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Survey On Aspect Based Sentiment Analysis Using Machine Learning Techniques

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Abstract; Web 2.0 facilitates the expression of views through diverse Internet applications which serve as a rich source of information. The textual expressions have latent information that when processed and analysed reveal the sentiment of the user/people. This is known as sentiment analysis, which is the process of computationally extracting the opinions and viewpoints from textual data and it is also known as opinion mining, review mining or attitude mining, etc. Aspect-level sentiment analysis is one among the three main types of sentiment analysis, where granule level processing takes place in which the different aspects of entities are harnessed to identify the sentiment orientations. The emergence of machine learning and deep learning techniques has made a striking mark towards aspect-oriented sentiment analysis. This paper presents a survey and review of different works from the recent literature on aspect-based sentiment analysis done using machine learning techniques.

KeywordsSentiment analysis, aspect based sentiment analysis, machine learning, deep learning

1. INTRODUCTION

Today, social media plays an important role in disseminating information on anything and everything within a matter of seconds. This prompted the common people to engage and interact in social media. The statistics of the year 2018 unleashed a jaw dropping figure of 500 million tweets in a year which can be rewritten as 6000 tweets per second thereby establishing Twitter as an active social platform. People share their feelings and opinions like the review of a product or service, etc., which eventually result in a huge amount of data on the Internet. This unstructured digital data contains lots of latent information which we can extract through Sentiment Analysis (SA). Reviews of customers have equalized the effect of word of mouth marketing in a way that the same drives the purchase decision of lakhs of customers geographically spread all over the world. A piece of text can literally impact the mind-set of a prospective buyer. It is utterly unwise possibility to process manually every review comment posted by numerous customers. SA is the perfect solution to be relied upon to analyse the trend underlying in any such purchase behaviour. Sentiment Analysis is one of the fast-growing research areas in Natural Language Processing (NLP). With the help of NLP, the process of extracting the attitude or opinions from a piece of text and classifying those on the basis of polarity like positive or negative or neutral is called SA. Unlike most of the research areas in NLP, SA is not a single problem; it is a suitcase of problems. Sentiment analysis is carried out at various granularities of documents like sentence, aspect and the document as a whole. Study of literature reveals comparative review and survey works on SA [62][63][64][66], but very few like Hai HA Do et al. [15] have consolidated the works on aspect-based sentiment analysis.

Further Sentiment Analysis is popularly carried out using Machine learning and Deep learning approaches. Hence, in this paper, we aim at presenting the various works that have used machine learning and deep learning approaches for the task of aspect-based sentiment analysis. This study also includes the significant domains and various datasets that have been focused in aspect based sentiment analysis.

The remainder of this paper is organized as follows: Section 2 presents a general overview of SA. Section 3 discusses the underlying concepts of aspect-based SA in detail. Section 4 presents the motivation and the need for this study. Section 5 discusses the different domains on aspect based sentiment analysis which SA research has been carried out and the corresponding datasets have been enumerated in section 6. Section 7 elaborates how machine learning and its variants have been used to identify the sentiments using aspects. Section 8 consolidates the research gap in aspect-based sentiment analysis. The conclusion is presented in section 9.

2. SENTIMENT ANALYSIS

2.1 Overview

One of the main objectives of SA task is to determine the polarity of the textual data. A textual data may have a tendency to lean towards positive or negative polarities. For example, "I really loved the film" is having a positive polarity and "That was the worst film I ever watched" is having a negative polarity. Sometimes, there may be sentences which don't convey any positive or negative polarities. Such sentences come under neutral polarity category. For example, “I neither loved nor hated that movie”. Sentences with factual information does not comes under neutral category.

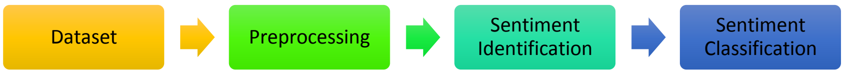


Figure 1 Steps in Sentiment analysis

For a normal SA task, there are mainly four steps (Figure 1), they are data collection, pre-processing, sentiment identification and sentiment classification. Data collection is simply acquiring raw text data in the form of reviews, blogs, discussion board data from various social networking platforms like Twitter, Facebook or e-commerce sites like Amazon, Flipkart recreation content sites like IMDB, Rotten Tomatoes, business review sites like Yellowpages, BBB, Yelp etc. These sources contain opinions or feeling on different entities expressed in different formats, size and style. In the next step, the necessary filtering processes are carried out to extract relevant data from the aforementioned datasets removing irrelevant content. Sentiment identification is the most important step in which sentences with subjective expressions need to be identified at the same time without ignoring sentences with implicit opinions.

Extraction of opinions from unstructured textual data is not a straightforward task to do. A sentence may contain a fact or an opinion, where the former one gives objective information on something and the latter one, gives the subjective information. One of the first tasks in SA is to classify a sentence as subjective or objective. Only subjective sentences that contain opinions are to be further look forward. Once the subjectivity classification is done, then the next task is polarity classification of subjective sentences to positive, negative or neutral polarity. As we are trying to extract opinions from textual documents, we can classify opinions into two different kinds, namely, direct or comparative opinions, and explicit or implicit opinions [65] [66]. Direct opinions express the sentiments in a straight forward way in the sentences. Unlike direct opinions, comparative opinions compare multiple entities or aspects within the sentence. On the other hand, an explicit opinion clearly and fully expresses the stand of a person regarding something leaving no room for the reader to read between the lines. While implicit opinion, at the same time, lacks clarity where the underlying meaning needs to be read to effectuate what was intended by that communication yet left unsaid. Unlike the former, implicit opinions have an extensive scope of employing metaphors which in turn make the whole process of analytics even more strenuous because of a lot of semantic information they are supposed to possess.

Finally, sentiment classification is the main task of SA where the subjective sentences are properly classified into the respective polarity types like positive, neutral or negative.

2.2 Granularity of the text

SA is not a single and simple task to solve as a series of tasks are there to confront. Sentiment analysis is carried out at various levels of text granularity like document, sentence and aspects as illustrated in Figure 2. Document-level SA is the simplest and basic type of SA, which tries to determine the overall sentiment polarity of the textual data. The very early works [67] [68] on SA were on the document level SA. Sentence level SA is a finer level of analysis when compared to document-level SA [69] [70]. Sentence level SA computes the sentiment polarity in the sentences of that document. Aspect level SA is fine-grained task of SA where different aspects describing the entity are identified from the document and further their corresponding sentiment words and polarity is determined.

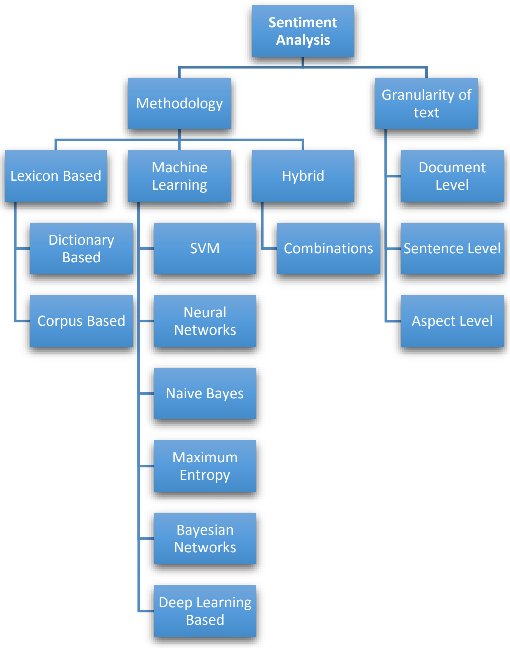


Figure 2 Classification of Sentiment analysis based on methodology and granularity

2.3 Methodology

Figure 2 enlists the three significant approaches for sentiment analysis viz. lexicon based, machine learning based and hybrid methods.

2.3.1 Lexicon based approach

SA can be done using lexicon based techniques which were practiced in the early works on SA [57] [58] [59] [75]. Lexicon based approach uses words that are annotated with polarity values, which gives the idea about the sentiment leaning of the textual content. One of the main advantages of this approach is that the training data is not required here and hence this is a unsupervised learning technique. But many expressions and words are not covered in this sentiment lexicons. Here, usage of lexical resources like SentiWordNet [60] or WordNet [61] etc. helps in the task of SA. Lexicon based approach can be further classified into two, namely dictionary based approach and corpus based approach. A dictionary which comprises opinion words backed up by their sentiment value is the construct in the dictionary based approach whereas context information replaces such dictionary in the corpus based approach. Corpus based approach is more into the probability of that word to be prefixed or suffixed with positive and negative adjectives. The major difference between dictionary-based and corpus-based is that the former one cannot determine the opinion words that having particular domain orientations while the latter one can find the same [76].

2.3.2 Machine learning approaches

Machine Learning (ML) algorithms creates models which are trained with the available data so as to predict or classify any unknown new input. These algorithms prove to provide results with higher accuracy. ML can be further categorized into mainly three levels viz. supervised learning, unsupervised learning and reinforcement learning. Under ML techniques, there are mainly two sets of data, namely training and test data. The training data is fed to a ML classifier for the training process. There are many classifiers like neural networks, NB, K-means, SVM, etc., which will make the necessary classifications predictions. For improving the classification accuracy, feature selection algorithms like Chi-square or Information Gain (IG) are used to rank the relevant set of features, so that the irrelevant features are not taken into consideration. After the training process, test data is given to a classifier to identify whether the machine learning model is giving desired outputs or not. Major machine learning approaches that are used in aspect based SA are discussed in section 6.

2.3.3 Hybrid approaches

There were many kinds of research having hybrid techniques that incorporate more than one approach for SA. One particular approach will be combined with another approach so that the final results will be more effective than the stand-alone approach. Many works [71] [72] [73] [74] combined lexicon-based and machine learning-based techniques to form a hybrid approach, where these hybrid techniques leverage both lexicon-based and machine learning algorithms.

2.4 Evaluation metrics

As the SA problem mainly focusses on the classification of words based on their sentiment polarity, evaluation of SA is done by the metrics - Precision (P), Recall (R), F-score (F1) and Accuracy (Acc). The primary task of SA by both the lexicon-based and machine learning-based approach is this classification task. Hence same evaluation metrics are used for both lexicon-based and machine learning-based approaches. Precision gives the percentage of relevant results, while recall finds the percentage of relevant results that are accurately classified by the SA model. F1 score calculates the overall accuracy of SA model using the aforementioned precision value and recall value. A good F1 score implies that the SA model shows less false-negative or false-positive, which means that the model is classifying much accurately. If the value of F1 score is 0, which means that the SA model is a complete failure, while the value 1 means that the model is giving the best performance. Accuracy is the ratio of the number of correct predictions to the total number of given inputs.

$$\text{Precision , P} = \frac{\text{True Positives}}{\text{Actual results}} \text{ or } \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\text{Recall, R} = \frac{\text{True Positives}}{\text{Predicted results}} \text{ or } \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

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

$$\text{Accuracy, Acc} = \frac{\text{True Positives} + \text{False Negatives}}{\text{Total}}$$

3. ASPECT BASED SENTIMENT ANALYSIS

Aspect based sentiment analysis (ABSA) [2] is a fine-grain level of SA task which tries to find the sentiment of various aspects of an entity within a textual data. In SA, an entity is a single identifiable object or a situation. It could be anything like an individual, place, movie or a product. In the textual data, the entity may be described using different sets of words aka features detailing the entities; these features are called '*aspects'* of the corresponding entity. The entity may be detailed though multiple aspects, and several supporting words or even sentences which convey some sentiments towards those aspects. ABSA strives to find the relevant aspects detailing the entity along with their upholding words and further determines the polarity or sentiment of those aspects. Consider the sentence, "*This guitar is looking so good, but the sound quality is not up to the expectation*". Here, the entity on focus is '*guitar*' and '*look*' and '*sound quality*' are the two aspects to be considered here. An ABSA for a sentence of this type has to tag a positive sentiment for the aspect '*look*', and a negative sentiment for the aspect '*sound quality*' as given in figure 3.

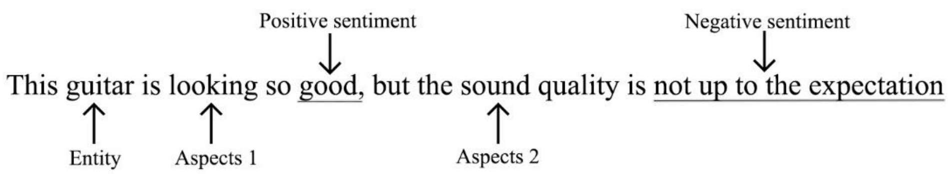


Figure 3 Identification of aspect sentiments

Similar to the general SA, ABSA also follows a multistage analysis. Many approaches and techniques have already shown their performance sequence of tasks. Figure 4 shows the workflow of ABSA, where the text data is first pre-processed to remove irrelevant words. In pre-processing, the given data should be made to a suitable format so that it can be further processed for the specific task. In SA, the data will be driven through a set of processing like tokenization, stop word removal, negation handling, etc., so that it is cleaned and converted to a suitable format. The process of converting the given text into a series of tokens is called tokenization. Tokenization helps in vector formation and the elimination of unwanted words from the text. Negation handling is an important pre-processing step because if it is not properly considered, the actual polarity orientation of the text will be the opposite of the outcome. Special characters, stand-alone punctuations and numerical tokens are removed since they do not convey any sentiment in the textual data. After tokenization, stemming is carried out, which tries to find the actual base word of given words in the textual data. After pre-processing word embedding is carried out, which is a very critical factor in SA using machine learning. The process of converting the token of words into a vector format is called word embedding. Words like 'aircraft' and 'airplane' are very similar, but there is a difference in meaning. To make a machine understand the difference in meaning, word embedding's are used, which will convert the text into another dimension. Further, these vectors fill be fed to a machine learning model for aspect and sentiment extractions. In the third stage, corresponding aspects of the entity from the texts are identified and then the contextual words that define the sentiment of the identified aspects are identified. In the final step, the sentiment orientation of sentiment words is identified accurately.

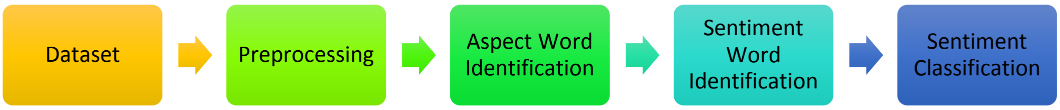


Figure 4 Work flow of aspect level sentiment analysis

Further, we can divide the task of ABSA into two, namely aspect category SA and aspect term SA [15]. Aspect category SA is a coarse-grained level of extraction of aspects and the latter one is a bit fine-grained level of extraction of the same. Example for aspect category SA is music, dance, etc. While on the other hand, drums, hip-hop dance, etc. are the examples of aspect term SA.

One of the main advantages of ABSA is its scalability. Because ABSA can easily analyse the textual data, automatically at a fine-grained level. The manual analysing task is a hectic one, as the huge amount of text is almost impossible to process in fine-grained level and also in a short span of time. Also, ABSA will be analysing aspects in texts like reviews, comments, etc., so that the companies or people can focus on those particular aspects where their customers are complaining or giving suggestions to improve their product or service. This will save a huge amount of time and money for the respective companies or people.

As ABSA comes under SA, it is also not a single problem to confront. Unlike the document level and sentence level sentiment analysis, ABSA gives more detailed and accurate results. The main three tasks of ABSA are aspect identification, identification of aspect supporting words and sentiment classification of those particular aspects. Today, the introduction of machine learning and deep learning techniques made it easy and efficient for analysing texts in ABSA. ML methods like SVM, CNN, LSTM, etc., used in many works for the task of ABSA [4][30][33].

4. METHODOLOGY

In ABSA, extraction of aspects and also the identification of corresponding sentiment words from the textual data is a challenging process. Further, polarity classification is the task of classifying sentiment words according to their polarity leaning like positive or negative or neutral. Many research works have done on this area and the introduction of machine learning approaches made promising results for the same. So there needs analysis of different works related to this area, which deals with various machine learning approaches, datasets, domains, etc. Hence, this paper discusses various works that have used machine learning approaches for the task of solving ABSA.

In this survey, 103 research articles are collected from the top journal publishers like Springer, Elsevier, etc. using the keyword - sentiment analysis and aspect-based sentiment analysis. From them, 66 articles are shortlisted based on the year of publishing. Most of the papers taken for consideration are from 2017 to till date. Out of them, 50 recent articles based on aspect level SA are taken for the review of literature (Refer table 1). Among these 50 research works, 43 are journal publications and 7 are conference proceeding papers.

Table 1 Year wise distributions of articles

Year	**Number of articles**	**Reference**
2010	1	[2]
2011	1	[5]
2012	2	[6][7]
2014	1	[50]
2016	3	[31][48][49]
2017	12	[10][23][26][27][29][34][41][42][43][45][46][47]
2018	18	[1][8][9][11][12][13][15][16][18][20][24][28][30][35][36][37][40][44]
2019	12	[3][4][14][17][19][21][22][25][32][33][38][39]

5. DOMAINS

This section discusses various domains that are normally used in ABSA. The domain is an important part when demystifying the SA, especially when the concentration is more on aspect level. It is the knowledge of domain that makes it easier, to extract the aspects from the given text. Because without the knowledge of context, it is difficult to distinguish the aspects from the text. Consider the examples on the domains-speaker and car, "speaker sound is so loud that everyone in that hall can hear it" and "car's engine is so loud". Here in the first example, according to the speaker, the loudness is giving a positive sentiment, while in the latter example; the loudness of the car's engine is giving a negative sentiment. So it is clear from the example that, domain knowledge is very important in the task of SA. i.e., the training data based on different domains will be an influential factor for the results of SA. To some extent, we can say that SA is domain-dependent. This conclusion is based on the reference to the literature review that has done here. It is clear that for each domain, there will be a different approach that makes better results on SA. The majority of the works on aspect level SA were on customer reviews on hotels, restaurants, movies, product reviews like laptops, TV, mobile phones, etc. Table 2 summarizes the various works on ABSA that are done on different domains.

Table 2 Works on ABSA over various domains & datasets

Domain	**Authors**	**Dataset used**	**Algorithm / Technique**
Blog writing	Xianghua Fu et al. [5]	SINA blog dataset	FCMN
TV reviews	Xianghua Fu et al. [6]	Manually collected Chineese TV online reviews	K-means+ Co-clustering
Product reviews	Lisette Garcuamaya et al. [7]	Manually collected product reviews	CNN

Electronic products	Aitor Garcia-Pablos et al. [34]	SemEval 2016 task 5	CRF
Twitter	Min Yang et al. [11]	Twitter, SINA	JABST and MaxEnt-JABST
Mobile phones	Reinaldkim et al. [12]	Amazon	Ensemble based on PSO
Product reviews	Sayed Mahdi et al.[13]	CR(Amazon), SST(Stanford sentiment treebank)	LSTM
Product reviews(mobile phones, digital camera, museum, telecommunications)	Md. Al Smadi et al.[16]	SemEval2016 task 5	Attention based LSTM
Camera, mobile, MP3 player, DVD player, restaurant, laptop	Ricardo Marcondes et al. [24]	7 benchmark datasets from two research papers	Stochastic language model
Notebok, Car, Camera, Phone	Haiyunpeng et al. [28]	4 Chinese datasets, SemEval2014	SVM and RNN
Musical instruments, smart phone	Jinming Zhang et al. [36]	Amazon	Hierarchical attention based LSTM
Customer reviews, Korean news articles	Minche song et al. [17]	Manually collected reviews, Wikipedia	Attention based LSTM
Electronics, Movies and TV, CDs and Vinyl and Clothing, Shoes and Jewelry	Hui Du et al. [49]	Amazon	CNN
Automobile	Chonghui Guo et al. [40]	Manually collected automobile reviews	Co-attention LSTM
Product reviews(AC, canister vaccum, coffee machine, DSLR, MP3 player, space heater)	Feilong Tang et al.[19]	Amazon	Feature enhanced attention network
Twitter	Chao Yang et al. [21]	Twitter	LDA
	Kariman et al. [22]	ASTD, MASTD, ArSAS, Arabic	AL-SSVAE

		gold standard twitter data for SA, Syrian tweets	
Movie reviews	Tun Thura Thet et al. [2]	IMDB	CNN, BiLSTM
	Deepa Anand et al. [31]	Manually collected movie reviews from IMDB & Amazon	
	Nurulhuda et. al [1]	Twitter	SVM
	Asha s manek et al.[4]	Cornell polarity dataset v1.0, Large movie review dataset V1.0, large movie review dataset SAR14	Attention based LSTM
	Sayed Mahdi et al.[13]	MR(IMBD), RT(Rotten tomatoes movies reviews)	LSTM
	Bowen Zhang et al.[14]	MR, SST1, SST2, CR, AFFR	LSTM
	Rajesh Piryani et al.[47]	IMDb	Linguistic approach
Hotel reviews	Md. Al Smadi et al.[16]	Manually collected Arabic hotel reviews	SVM
	NadeemAkthar et al.[23]	Manually collected hotel review dataset	LDA, DP, CR, and NER NLP tools
	Duc-hongpham et al.[29]	Hotel reviews from tripadvisor.com	CNN
	Aitor Garcia-Pablos et al.[34]	SemEval 2016 task 5	CRF
	Md. Al Smadi et al.[10]	Arabic hotel reviews-SemEval2016 task 5	Attention based LSTM
	Ravindra Kumar et al. [3]	Manually collected reviews from booking.com	Neural network

	Aitor Garcia-Pablos et al. [34]	SemEval 2016 task 5	CRF
Restaurants, Laptop	Ruizin Ma et al.[26]	SemEval 2014	LDA
	Md Shah Akhtar et al.[27]	SemEval 2014	LDA
	Ruidan He et al.[8]	SemEval2014, SemEval2015, 2016	Attention based LSTM
	Md. Al Smadi et al.[10]	SemEval2016 task 5	Attention based LSTM
	Xia ma et al.[18]	SemEval 2014	LSTM
	Md. Al Smadi et al.[10]	SemEval2016 task 5	Attention based LSTM
	Feilong Tang et al.[19]	Yelp	Feature enhanced attention network
	ParamitaRay et al.[25]	SemEval 2014 task 4	LSTM
	Chao Yang et al.[21]	SemEval2014	LDA
	Lisette et al.[32]	SemEval 2016 task 5	SVM, Logistic regression and RNN
	WeiduXu et al.[33]	SemEval2014 task 4	CNN
	Jiangfengzeng et al.[38]	SemEval 2014	SVM
	Yi Tay et al.[42]	SemEval 2014 Task 4, SemEval 2015 Task 12, SemEval 2016 Task 5	Tensor DymenNN
	Jianhua Yuan et al.[45]	SemEval 2014	LSTM
	Hai Ye et al.[46]	SemEval2014 Task4	LSTM
Laptop	Reinald Kim et al.[12]	Amazon	Ensemble based on PSO
	Hu Han et al. [37]	SemEval 2014	Linguistic approach
	ANH-DUNG VO et al.[35]	Manually collected laptop	LDA

		reviews	
Restaurants	Jiangtaoqiu et al.[20]	Yelp	LDA
	Duc-hongpham et al.[30]	Manually collected restaurant reviews	LSTM
	Aitor Garcia-Pablos et al. [34]	SemEval 2016 task 5	CRF
	Wei Xue et al.[41]	SemEval 2014 Task 4, SemEval 2015 Task 12, SemEval 2016 Task 5	BiLSTM + CNN

6. DATASETS

Aspect based sentiment analysis focus on review sort of data as they are rich in opinions about the different features of the products under review. Customer reviews are like product reviews from Amazon, Flipkart, etc., or movie reviews from IMDB or Rotten Tomatoes, etc., or Twitter tweets on a specific product or service, etc. One of the early problems for carrying out ABSA is the lack of benchmark datasets. In recent years, more researches in this field resulted in some good publically available datasets which is presented in Table 3. In 2014, Pontiki et al. [51] created a dataset particularly for ABSA called SemEval 2014 task 4. In SemEval 2015 dataset, Pontiki et al. [52] included hotel reviews along with reviews on the laptop and reviews on restaurants again in English language. Again, Pontiki et al. [53] created a dataset called SemEval 2016 that included reviews not just in English but also Arabic, Chinese, Dutch, French, Russian, Spanish and Turkish. This dataset contains reviews on laptops, hotels, cameras, mobile phones, and restaurants. In 2014, Dong et al. [54] created a Twitter-based dataset called target-dependent twitter sentiment classification dataset which contains 6,940 tweets. Maia et al. [79] created a financial news-related dataset called FiQA ABSA. This dataset contains financial micro blogs and samples on financial news headlines. Kessler et al. [55] developed a dataset called ICWSM 2010 JDPA Sentiment corpus. This dataset includes documents related to automotive and digital devices. Toprak et al. [56] created Darmstadt Service Review Corpus dataset that contains reviews on online universities and their services.

Table 3 ABSA Datasets

No.	Name of the Dataset	Domain	Language	Number of reviews/tweets/micro blogs
1	SemEval 2014	Restaurant, laptops	English	Restaurant – 3841 Laptops - 3845
2	SemEval 2015	Hotel, restaurant, laptops	English	Hotel – 30 Restaurant – 350 Laptops – 450
3	SemEval 2016	Hotel,	English, Arabic,	Laptop – 350

		restaurant, laptops, mobile, camera	Chinese, Dutch, French, Russian, Spanish and Turkish	(English) Hotel – 2291 (Arabic) Camera – 200 (Chinese) Mobile – 200 (Chinese), 270 (Dutch) Restaurant – 339 (Turkish), 313 (Russian), 555 (French), 400 (Dutch), 913 (Spanish)
4	Target-dependent twitter sentiment classification dataset	Tweets	English	6,940
5	FiQA ABSA	Financial micro blogs and financial news headlines	English	Micro blogs – 774 News headlines – 529
6	ICWSM 2010 JDPA Sentiment corpus	Automotive and digital devices	English	515
7	Darmstadt Service Review Corpus	Online universities and their services	English	118

In the next section, different machine learning approaches that are used for solving ABSA are discussed.

7. MACHINE LEARNING (ML) APPROACHES FOR ABSA

ML algorithms have been considered to work accurately with respect to aspect based sentiment analysis. The following sub sections present the different ML algorithms and their suitability for ABSA.

7.1 Latent Dirichlet Allocation (LDA)

LDA or Latent Dirichlet Allocation is a generative, probabilistic model for a set of documents, which are described as combinations of latent topics. LDA, which is a topic modelling technique, helps in automatically finding the underlying topics from a given document. LDA considers documents as mixtures of topics with words having particular probabilities. Xianghua Fu et al. [5] used Kull-back-Leibler (KL) divergence for finding the relationship between given paragraphs and theme models, where the principal objective was to determine the theme of the paragraph. The authors used the LDA model to identify the theme of blogs and they used KL divergence to determine the distance among the themes. Nadeem Akthar et al. [23] used a topic modelling tool called Mallet, where they used LDA to determine the latent information and aspects from a manually collected hotel reviews. Aitor Garcia-Pablos et al. [34] proposed W2VLDA, which is an unsupervised system that deals with multi-domain and multilingual ABSA. W2VLDA uses a huge amount of unlabelled textual data and the initial configuration is with a minimum set of seed words. Authors used LDA topic modelling combined with an unsupervised pre-trained classification model for aspect identification and separation of opinion-words. Reinald Kim et al. [12] have designed a Aspect Sentiment Unification Model (ASUM) by including product descriptions. ASUM is a modified version of LDA which consolidates both aspect and its corresponding sentiment [77]. They have proposed two extensions to ASUM viz. SA-ASUM (Seller-Aided Aspect-based Sentiment Model) and SA-PSM (Seller-Aided Product-based Sentiment Model). When comparing to other topic modelling, these two models achieved better performance. Authors used Amazon reviews on laptops and mobile phones for the experimental conclusions. Chonghui Guo et al. [40] proposed a ranking method incorporating different aspects of different product reviews. Subjective and objective sentiment values are used in this work. To fuse different online reviews, the authors constructed a directed graph model. The textual visualization and LDA topic modelling are applied to obtain the values of nodes in this directed graph. Here in this work, the improved PageRank algorithm not only used online reviews, but also consumer preferences, which improved the overall result.

7.2 Conditional Random Field (CRF)

Unlike generative models like LDA, Conditional Random Fields (CRF) is a discriminative model which is used for prophesying sequences. In CRF, information obtained from the prior labels is used for more accurate prediction. Jiangtao Qiu et al.[20] proposed a predictive framework for determining the ratings of non-rated reviews from Yelp dataset. Authors used a variant of CRF called sentiCRF for pair term generation and for finding their sentiment scores. To predict the rating of a review, they introduced a cumulative logit model which takes aspects and their corresponding sentiment values from the reviews. Further, to solve the class imbalance problem at the time of the sentiment score estimation, they proposed a heuristic re-sampling algorithm.

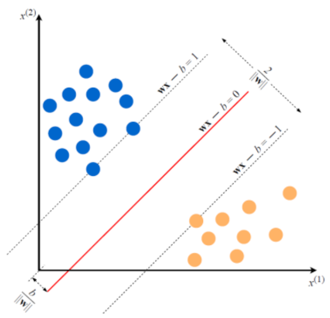
7.3 Support Vector Machine (SVM)

For the task of classification and regression, SVM is a promising supervised machine learning algorithm. In SVM, every data item will be plotted on an n-dimensional graph and a hyper plane will be drawn based on the task of classification or regression. Amidst the possible hyper planes, the one with the highest distance from the support vectors will be considered as a hyper plane.

$$\vec{w}\cdot\vec{x}+b=0$$

$$\vec{w}\cdot\vec{x}+b=1$$

$$\vec{w}\cdot\vec{x}+b=-1$$



e 5 SVM

For the task of aspect term extraction on large movie reviews, Asha S Manek et al.[4] compared five feature selection algorithms including SVM and Naive Bayes (NB) classifiers and found that SVM is giving the best results with the Gini Index feature selection algorithm. Nurulhuda et al. [1] proposed a hybrid sentiment classification model that used SVM along with an Association Rule Mining (ARM) technique. Feature selection methods like PCA (Principal Component Analysis), Latent Sentiment Analysis, random project, etc. are applied with a heuristic combination of Parts Of Speech (POS) and also for the extraction of implicit aspects, the authors used Stanford Dependency parser in this work. Muhammed Al Smadi et al. [16] proposed a model that improved the task of ABSA on hotel reviews in Arabic language. They used syntactic, semantic, and morphological features for the same and they compared different classification models like NB, SVM, Bayes network, K-Nearest Neighbour (KNN), Decision Tree (DT) and found that SVM is giving the best results out of them. Muhammed Al Smadi et al. [10] evaluated RNN with SVM on ABSA on Arabic hotel reviews. The authors used a vector space modelling tool named Gensim in their proposed work. On the manually collected hotel reviews, evaluation results showed that SVM outperformed RNN, but in terms of training and testing, RNN was more reliable. Kariman et al. [22] proposed HILATSA (Hybrid Incremental Learning Approach for Arabic Tweets Sentiment Analysis). This approach is a combination of lexicon-based and machine learning in which lexicons and machine learning algorithms like SVM, logistic regression and RNN, are used to extract sentiments from tweets in Arabic language.

7.4 Convolutional Neural Network (CNN)

CNN is a feed forward neural network which was mainly used in image processing which later on used in almost all other areas. The input to the CNN model will be passed through many convolutional layers with filters called kernels, pooling, Fully Connected layers (FC), and further softmax function concludes the final value to a probabilistic value between 0 and 1. The very first layer is the convolutional layer which extracts all the features from the given input. To tackle the problem of non-linearity in ConvNet (Convolutional Neural Network), ReLu (Rectified Linear Unit for a non-linear operation) functions were introduced. Ravindra Kumar et al. [3] applied CNN for the task of ABSA and also stochastic optimization was done in their work. Here semantic feature extraction was done by developing ontologies and word-level embedding is done using word2vec. Authors introduced Particle Swarm Optimization (PSO) in multi-objective function for parameter tuning in CNN. Sayed Mahdi Rezaeinia et al. [13] proposed Improved Word Vectors (IWV), an approach that improved the accuracy of pre-trained word embedding's - Word2Vec and Glove. Word2Vec and Glove convert text into numerical values called vectors which will be fed to neural networks or deep neural networks. Word2Vec is a two-layer feed forward neural network that converts words and expressions to vector dimension. In Glove, the matrix factorization method is performed over the matrix of word-context. Authors incorporated mainly four approaches in their work; they are Word2Vec/Glove, POS, word position algorithm, and lexicon-based approach. Bowen Zhang et al. [14] used critic learning in the optimization of CNN for SA. This critic learning can learn the significance of knowledge rules and further use them accordingly. The authors used two branch CNN where each branch consists of one predictor. Here the first one uses the textual features and the latter one uses the given or designed knowledge rules. First order logic (FOL) rules are employed in this framework to control the predictors. Paramita Ray et al. [25] combined a deep learning method along with rule based methods to enhance the task of ABSA and also to improve the performance of sentiment scoring method. For the aspect identification from laptop and restaurant reviews, a seven-layer CNN has been used. Duc Hong Pham et al. [30] proposed an approach that incorporated various word embedding methods with one-hot character vectors for aspect level SA. The proposed model called the Multichannel framework using CNN (MCNN) where every single representation of input is controlled by a single CNN alone. The one-hot character vector, Glove, and word2vec word embedding methods are used in this work.

7.5 Long Short Term Memory (LSTM)

Long Short Term Memory (LSTM) network is a type of Recurrent Neural Network (RNN), which is developed to resolve the issues that RNN had; vanishing gradient and exploding gradient problem. The major benefit of LSTM is that it is intelligent enough to learn long term dependencies. That is LSTMs are able to remember the information for a longer amount of time. For this, LSTM added an explicit memory unit called cell in its network. LSTM takes three inputs, current input, previous output, and previous memory and further makes the decision based on these inputs. Xia Ma et al. [18] proposed an approach based on LSTM which is having a two-stage aspect level classification of sentiments. The first model tries to extract aspects from the context words and the second one analyses and extracts the multiple aspects from the sentences with various opinions. Weidu Xu et al. [33] developed a generative model for aspect level sentiment classification that used LSTM over restaurant and laptop reviews. It is a semi-supervised approach that contains two stochastic variables viz. sentiment and context. Irum Sidhu et al. [39] proposed an ABSA on student's feedback for the performance evaluation of teaching faculty. The authors used a two layer LSTM model for the aforementioned task, where the task of first layer is to classify the review sentence into six predefined aspects, while the second one predicts the polarity of the previous aspects. Ruidan He et al. [8] utilized document knowledge for aspect identification and sentiment classification. For this, they used two transfer methods called pre-training and multi-task learning. They used the attention-based LSTM network in their approach. Minche Song et al. [17] proposed lexicon embedding in the task of aspect level SA that used the attention-based LSTM network. They used news articles, customer reviews, and Wikipedia in the Korean language for this task. Jiangfeng Zeng et al. [38] proposed a new attention-based LSTM model called dubbed PosATT-LSTM that incorporates context information as well as position contexts for aspect and sentiment extraction. They worked on restaurant and laptop reviews from SemEval 2014 dataset.

Table 4 Accuracy reported on various ML works

Authors	**Algorithm / Technique**	**Accuracy/F1 score**
Nurulhuda Zainuddin et al. [1]	SVM + ARM	76.55%
Tun Thura Thet et al. [2]	CNN, BiLSTM	Overall movie- 86% Director- 86% Cast- 83% Story- 80% Scene- 90% Music- 81%
Ravindra Kumar et al. [3]	Neural network	88.52%,
Asha S Manek et al. [4]	Attention based LSTM	97.32%
Xianghua Fu et al. [5]	LDA	89.165%
Xianghua Fu et al. [6]	K-means+ Co-clustering	78.198%

Ruidan He et al.[8]	Attention based LSTM	85.58%
Yukun Ma et al. [9]	Hierarchical attention based LSTM	89.32% on SentiHood dataset 76.47% on SemEval 2015 dataset
Mohammad Al-Smadi et al. [10]	Attention based LSTM	95.4%
Min Yang et al. [11]	JABST and MaxEnt-JABST	Twitter dataset- 71.2% Sina dataset- 69.8%
Reinald Kim et al. [12]	Ensemble based on PSO	85.73%
Sayed Mahdi et al. [13]	LSTM	Customer review- 85.1% Movie review- 81.5% Stanford Sentiment Treebank(SST1) - 87% Rotten Tomatoes- 82% SST-2 (same as SST1 but with fine-grained labels)- 46.2%
Md. Al Smadi et al. [16]	SVM	95.4%
Minche song et al. [17]	Attention based LSTM	Wikipedia- 91.28% Customer reviews- 92.91% News articles- 92.07%
Xia Ma et al. [18]	LSTM	Laptop- 73.1% Restaurant- 80.1
Feilong Tang et al. [19]	JABST and MaxEnt-JABST	Amazon- 83% Yelp- 85%
Jiangtao qiu et al. [20]	CRF	93.6%
Chao Yang et al. [21]	Coattention LSTM	Restaurant- 78.8% Laptop- 73.5% Twitter- 71.5%
Kariman et al. [22]	SVM, Logistic regression and RNN	83.73%
Paramita Ray et al. [25]	CNN	87%
Ruizin Ma et al.[26]	FCMN	Restaurant- 82.03% Laptop- 73.94%
Md Shah Akhtar et al.	Ensemble based on	Restaurant- 80.07 %

[27]	PSO	Laptop- 75.22 %
Haiyun Peng et al. [28]	ATSM-F	85.95%
Duc-Hong Pham et al. [30]	CNN	84.16%
Xianghua Fu et. al. [32]	AL-SSVAE, attention based LSTM	88.98%
Weidu Xu et al. [33]	LSTM	81.76%
Hu Han et al. [37]	CNN, BiLSTM	Restaurant- 72.41 % Laptop- 80.96%
Jiangfeng Zeng et al. [38]	Attentive LSTM	Restaurant- 72.8 % Laptop- 79.4%
Irum Sindhu et al [39]	LSTM	Sentiment orientation detection- 93% Aspect extraction- 91%
Wei Xue et al. [41]	LDA	88.91%
Yi Tay et al. [42]	BiLSTM	Customer review- 85.4% Movie review- 82.3% Stanford Sentiment Treebank(SST1) – 48.5% SST-2 (same as SST1 but with fine-grained labels)- 88.3%
Hui Du et al. [49]	CNN	92.93%

These are the major machine learning techniques that are used for solving ABSA and these techniques have shown promising results when compared to other NLP based methods. Table 4 consolidates the accuracy of various ML works on ABSA.

8. CHALLENGES

ABSA, a fine-grained level of SA has made its great influence in the current technology-oriented world in the past four to five years. This paper discussed few papers on this area and when comparing the methodologies that are followed by various authors, it is clear that deep learning works are giving more promising results on aspect level SA. But still, some works show that deep learning methods are outperformed by machine learning methods. For example, Muhammed Al Smadi et al. [10] pointed out that SVM is showing better results over RNN [10]. In contemporary society, SA has a great level of importance in different applications like analysing customer feedback. So the domain is a critical factor for aspect level SA. From the works discussed in this paper, it is clear that most of the research works are focussing more on the same domains, for example, laptops, restaurants, hotels, etc. Many other domains like travel reviews, news, etc., that are having a high level of significance are still under untouched research areas. Also, the lack of benchmark datasets on different domains is a serious problem for researches in this area. One other important problem is the language in which SA is being done. Only a few languages like English, Chinese, etc. are being actively participating in SA tasks, while the regional language is very rarely used for SA. The active participation of usage of regional language in social media gave a significant level of importance to this area to have more researches in aspect level SA. Lack of good datasets in regional languages is also becoming a hindrance to further researches in this area.

9. CONCLUSION

SA is the process of extracting the opinions, emotions or feelings from a piece of text, which has made its signature in the modern e-world. Within SA, three levels of granularities are there, called document level, sentence level, and aspect level SA. The third one, ABSA is a much finer level of analysis where extractions of aspects and corresponding sentiments words and also the extraction of their polarity orientations are taken place. ABSA is trying to stand on its feet now as many research works have already done over it in the past three to four years. The introduction of machine learning had made a serious impact on the level of perception and complexness in SA. One major issue with ABSA is the lack of benchmark dataset and those datasets that are publically available are covering fewer domains only. Because of the technological advancements, deep learning methods are giving some level of promising results for ABSA, but still, it is obvious from the literature survey that the results are not up to the expectation. In other words, we can say that ABSA with deep learning is in the beginning stages of unfolding.

10. **REFERENCE**

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