# Issues and Challenges of Aspect-based Sentiment Analysis: A Comprehensive Survey

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**Abstract**—The domain of Aspect-based Sentiment Analysis, in which aspects are extracted, their sentiments are analysed and sentiments are evolved over time, is getting much attention with increasing feedback of public and customers on social media. The immense advancements in this field urged the researchers to devise new techniques and approaches, each sermonizing a different research analysis/question, that cope with upcoming issues and complex scenarios of Aspect-based Sentiment Analysis. Therefore, this survey emphasized on the issues and challenges that are related to extraction of different aspects and their relevant sentiments, relational mapping between aspects, interactions, dependencies, and contextual-semantic relationships between different data objects for improved sentiment accuracy, and prediction of sentiment evolution dynamicity. A rigorous overview of the recent progress is summarized based on whether they contributed towards highlighting and mitigating the issue of Aspect Extraction, Aspect Sentiment Analysis or Sentiment Evolution. The reported performance for each scrutinized study of Aspect Extraction and Aspect Sentiment Analysis is also given, showing the quantitative evaluation of the proposed approach. Future research directions are proposed and discussed, by critically analysing the presented recent solutions, that will be helpful for researchers and beneficial for improving sentiment classification at aspect-level.

**Index Terms**—Aspect, computational linguistic, deep learning, sentiment analysis, sentiment evolution, social media

## 1. Introduction

The field of Natural Language Processing (NLP) dealing Sentiment Analysis (SA), also named as opinion mining, is an active research area to display emotions and to automatically discover the sentiments expressed within the text [1]. The object of SA is usually a product or service that is of keen interest among people, that they care to put a sentiment towards it. Traditionally, SA has been considered as an opinion polarity that whether someone has expressed positive, negative or neutral sentiment about an event [2].

Since last decade, researchers are putting efforts to capture, quantify and measure dynamic public sentiments through different methods, tools and techniques, and thus allowing SA as one of the rapidly growing research areas [3]. SA applications have been widely spread to nearly every domain, like social events, consumer products and services, healthcare, political elections and financial services. Influential groups and business organizations, like, Google, Microsoft, SAP and SAS, have designed their own in-house capabilities that support them in decision making and assist them in developing better business applications to track and predict evolving market trends.

From studies, SA has been generally categorized at three levels. Document-level [4], sentence-level [5] and aspect-level SA [6] to classify whether a whole document, a sentence (subjective or objective) and an aspect express a sentiment, i.e., positive, negative or neutral. The Aspect-based Sentiment Analysis (AbSA) helps to understand the problem of SA better comparatively, because it directly focuses on sentiments rather than language structure.

Where, an aspect is related to an entity, and the basic concept of an aspect is not just limited to judgement but also extends towards thoughts, point of views, ways of thinking, perspectives, an underlying theme or social influence towards an occurrence. Hence, AbSA provides a great opportunity to analyse sentiments (public) over time across different contents present on media [7].

AbSA can be categorized by three main processing phases, i.e., Aspect Extraction (AE), Aspect Sentiment Analysis (ASA) and Sentiment Evolution (SE). The first phase deals with the extraction of aspects, which can be explicit aspects [8], implicit aspects [9], aspect terms [10], entities [11] and Opinion Target Expressions (OTE) [12]. The second phase classifies sentiment polarity for a predefined aspect, target or entity [13]. This phase also formulates interactions, dependencies and contextual-semantic relationships between different data objects, e.g., aspect, entity, target, multi-word target, sentiment word, for achieving improved sentiment classification accuracy [14], [15]. The expressed sentiment can be classified into ternary, or fine-gained sentiment values [2], [16]. The third phase concerns with the dynamicity of peoples' sentiment towards aspects (events) over a period of time. Social characteristics and self-experience are considered as the leading causes for SE [17].

### 1.1 Focus of This Survey

The field of AbSA is not a straight road, it has suffered many diverse changes and touched many new eras to ponder over. Researchers have been working hard to resolve multi-faceted

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*Manuscript received 26 May 2019; revised 21 Nov. 2019; accepted 19 Jan. 2020. Date of publication 30 Jan. 2020; date of current version 31 May 2022.*
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*Recommended for acceptance by C. Girju.*
*Digital Object Identifier no. 10.1109/TAFFC.2020.2970399*

challenges containing many issues. They have come up with thorough solutions of many complicated challenges through different machine-learning techniques, mostly deep-learning techniques, that represent their critical idea in the field. They have provided pictorial representations and numerical modeling for handling complex scenarios through different attention mechanisms and neural-memory networks. For detailed knowledge on deep-learning techniques, attention mechanisms and memory networks, we refer our readers to these surveys [18], [29], [30], [31].

Therefore, a comprehensive survey is the need of time to summarize the most recent developments in the field of AbSA. The focus of existing surveys is limited to the technical details or specific phases of AbSA. The critical issues and key challenges of AE, ASA, SE have not stated and summarized accurately. Those surveys have also become outdated because of the exponential achievements and innovations in recent years. To fill this gap, we propose a comprehensive survey related to AbSA.

Our survey presents the systematic, detailed and thorough study about existing issues (challenges) of AE, ASA and SE, and their assembled solutions in most recent years. The survey also proposes new suggestions that induce some serious thoughts and considerations to improve present solutions, which would be helpful for future research directions; along with considering how SE is an important and exciting research problem for many applications.

Based on the present study, the fundamental prospects are discovered and discussed that are essential for future advancements and developments, as they will provide an immense-boost and motivation for researchers to explore and devise new approaches that will overcome the critical issues and major challenges of AbSA. Table 1 presents a brief summary of some existing surveys (related to AbSA and SA) and our survey.

### 1.2 Organization of This Survey

The survey has been started with the brief introduction and paramount significance of AbSA. The rest of the survey is organized as follows: Section 2 provides the definitions of sentiment with respect to aspect, and lists down the major issues and challenges related to AE, ASA and SE. Sections 3 and 4 discusses the major issues of AE and ASA, and concisely describes the recent solutions for these issues. Section 5 discusses the dynamics of SE. Section 6 highlights the future research directions. Section 7 concludes this survey.

## 2. Key Solutions

This section presents AbSA definitions, and outlines the major issues and sub-issues of AE, ASA and SE. This section also illustrates three main processing steps of AbSA, i.e., AE, ASA and SE, through framework for the ease and understandability of the reader.

### 2.1 Definitions (AbSA)

In AbSA, sentiment is a subjective consciousness of human beings towards an aspect (objective existence). People get affected by the ups and downs of life, at any time and place, which results in the change of their sentiment towards a specific aspect. This change depicts human behavior flexibility, decision autonomy and creative thinking. Pang and Lee [19] defined SA as: "A sentiment is basically an opinion that a person expresses towards an aspect, entity, person, event, feature, object, or a certain target." Now days, researchers mostly use the term 'aspect' instead of 'feature' for specific application.

Liu [5] defined the above terms like: 'an opinion is defined as a quintuple $(\mathrm{e_i}, \mathrm{a_{ij}}, \mathrm{s_{ijkl}}, \mathrm{h_k}, \mathrm{t_l})$, where $\mathrm{e_i}$ is an entity, object or person, $\mathrm{a_{ij}}$ is the $j^{\text{th}}$ aspect of $\mathrm{e_i}$, $\mathrm{s_{ijkl}}$ represents sentiment that an opinion holder $\mathrm{h_k}$ expresses at time t for $\mathrm{a_{ij}} \in \mathrm{e_i}$. $\mathrm{s_{ijkl}}$ could be positive, negative or neutral. Both $\mathrm{e_i}$ and $\mathrm{a_{ij}}$ collectively become the opinion target.

### 2.2 The Core Issues and Challenges of AbSA

In the light of above definitions, the big issues and major challenges facing by AbSA are basically the elements which constitute these definitions. These major issues and sub-issues that are discussed in this survey are listed below:

1. How to perform the process of AE effectively; why till now this remains a big challenge?
   - i. How to extract explicit aspects, OTE, implicit aspects and aspects with neutral sentiment?
   - ii. How to perform cross-domain and cross-lingual AE?
   - iii. How to map relationships between different data objects for improved AE?
2. How to conduct ASA; how to achieve a sentimental-calculation model that performs an in-depth analysis of all the emotional aspects; why this is still a big challenge and hot research area?
   - i. How to perform SA at aspect (target), entity and multi-word-target level?
   - ii. How multi-task learning enhances the sentiment prediction accuracy?
   - iii. How the interactions, dependencies and contextual-semantic relationships between data objects contribute towards improved sentiment classification?
3. How to measure the change of sentiment value with time; why there is not any outstanding achievement which makes SE an open issue?
   - i. How to identify factors and track obvious deficiencies in continuously-changing- sentimental characteristics?
   - ii. How to predict SE over Social Data?

These three issues are the core of AbSA and excellence could be achieved by resolving each issue at granular-level. Fig. 1 illustrates these three main phases (issues) of AbSA, i.e., AE, ASA and SE, with an initial necessary preprocessing step that applies the preprocessing filters, e.g., tokenization, transforming cases, stemming and filtering of stop words, on the corpus for eliminating any needless information, e.g., special characters, stop words, repeated words, etc. [32]. The following step is to transform the data into word embeddings, e.g., word2vec [33], Glove [34], ELMo [35], Bert [36], and then compute positional information of words, accordingly [29].

## 3 Aspect Extraction (AE)

AE deals with detection and discovery of explicit aspects, implicit aspects, entities, aspect categories and OTE. AE

TABLE 1
An Overview of Existing Surveys and Our Survey

| Author | Title | Critical Idea | Challenges |
|---|---|---|---|
| Pang *et al.* 2008 [19] | Opinion Mining and SA | • presented applications that determine sentiment of the document, and organized approaches related to opinion-oriented classification problems | How to perform SA at document-level using machine-learning approaches? |
| Tang *et al.* 2009 [20] | A Survey on Sentiment Detection of Reviews | • discussed approaches related to subjectivity classification, word classification and opinion discovery in customer-review domain | How to perform SA at document-level using machine-learning approaches? |
| Wiegand *et al.* 2010 [21] | A Survey on the Role of Negation in SA | • presented computational methods for handling negation in SA | How to cope with the scope and challenges of negation modeling? |
| Tsytsarau *et al.* 2012 [22] | Survey on Mining Subjective Data on The Web | • differentiated between four different approaches that classify word-sentiment value, i.e., machine-learning, semantic, statistical and dictionary-based approaches | How to perform subjective SA at document-level? |
| Liu 2012 [2] | SA and Opinion Mining | • covered the field of SA at document, sentence and aspect-level<br>• discussed various issues related to AE, sentiment classification, sentiment lexicons, NLP and opinion-spam detection<br>• surveyed the till date practical solutions along with the future directions | How to cope with review ranking, redundancy issues, viewpoints quality, genuine aspects, spammer detection etc...? |
| Ravi *et al.* 2015 [23] | A Survey on Opinion Mining and SA: Tasks, Approaches and Applications | • organized subtasks of machine-learning, NLP and SA techniques, such as, subjectivity classification, sentiment classification, lexicon relation, opinion-word extraction, and various applications of SA<br>• discussed open issues and future directions in SA | How to focus on sentence-level and document-level SA and their subtasks? |
| Giachanou *et al.* 2016 [24] | Like It or Not: A Survey of Twitter SA Methods | • discussed the deep-learning algorithms related to twitter SA<br>• laborated tasks specific to emotion detection, change of sentiment over time, sarcasm detection, and sentiment classification | How to tackle the challenges, tasks and feature selection methods limited to twitter SA? |
| Schouten *et al.* 2016 [6] | Survey on Aspect-Level SA | • performed approach-based categorization of different solutions those were related to AE, aspect classification and a combination of both<br>• proposed future research direction for semantically-rich-concept-centric AbSA | How to cope with the challenges of compar-ative opinions, conditional sentences, negation modifiers and presentation? |
| Zhang *et al.* 2018 [25] | Deep Learning for SA: A Survey | • presented applications and deep-learning approaches for the SA related tasks such as sentiment intersubjectivity, lexicon expansion, stance detection | How to achieve advances in SA using deep-learning approaches? |
| Zimbra *et al.* 2018 [26] | The State-of-the-Art in Twitter SA: A Review and Benchmark Evaluation | • focused on challenges and key trends related to classification errors, twitter monitoring and event detection to perform twitter SA effectively | How to reveal the root causes of commonly occurring classification errors? |
| Yue *et al.* 2018 [27] | A Survey of SA in Social Media | • categorized the latest technologies and techniques in SA<br>• introduced latest tools for research approaches related to subjectivity classification in customer-review domain | How to focus on different types of data and advance tools, to overcome the limitations of social media SA? |
| Kim and Klinger 2018 [28] | A Survey on Sentiment and E-motion Analysis for Computational Literary Studies | • presented approaches of SA and emotion analysis<br>• discussed the computational methods for sentiment and emotion classification | How to classify and interpret the emotional text through sentimental and emotional analysis in digital human community? |
| Our | Issues and Challenges of Aspect-based Sentiment Analysis: A Comprehensive Survey | • discusses the issues and challenges of AE, ASA and SE<br>• presents the progress of AbSA by concisely describing the recent solutions<br>• highlight factors responsible for SE dynamicity<br>• proposes future research directions by critically analysing the present solutions | How to improve the mechanism of AE?<br>What measures should be taken to achieve good classification accuracy at aspect-level?<br>How to predict SE dynamicity? |

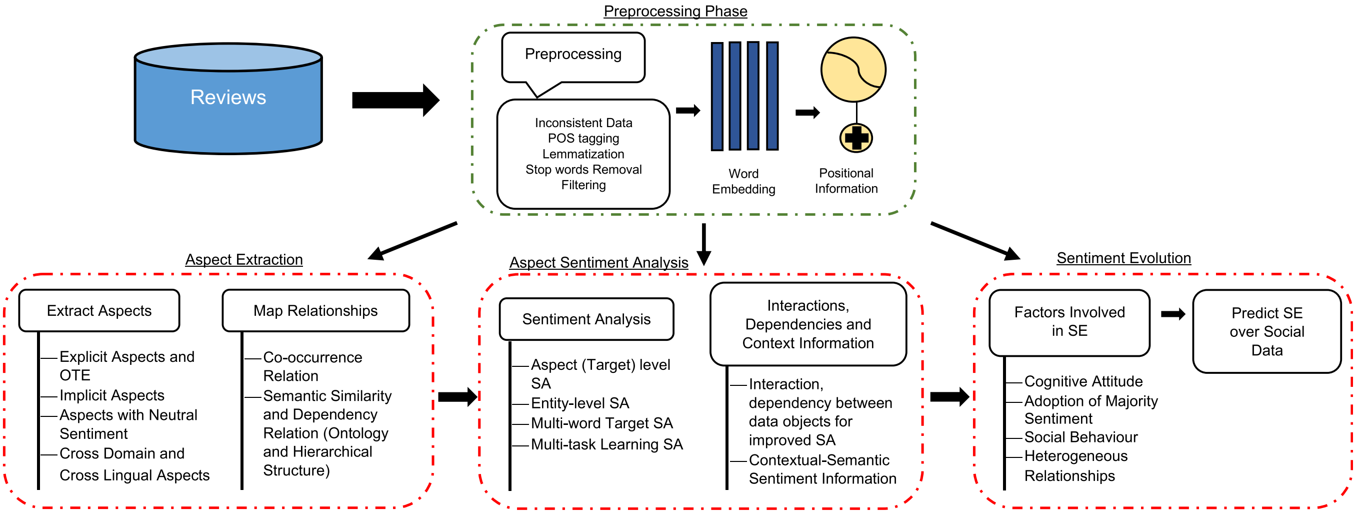


Fig. 1. A framework regarding the main phases of aspect-based sentiment analysis

also tackles the relation distribution between different aspects in order to identify consistent, coherent and similar aspects from the dataset that help in improving the overall representation of extracted aspects. All solutions featuring the extraction of aspects and relational mapping between aspects are discussed in this section and Table 2.

## 3.1 Extraction of Aspects

### *3.1.1 Explicit Aspects and OTE Extraction*

The foremost crucial issue towards AE is; the extraction of explicit aspects, entities, aspect categories and OTE upon which a sentiment is being expressed. Where, an explicit aspect means that it is present in the text, e.g., "the camera of this mobile phone is great" is an example of an explicit aspect, i.e., camera, and explicit entity, i.e., mobile phone. Aspect category combines entity, and aspect of that entity into a pair, e.g., "This mobile looks great but expensive", in this example "MOBILE#APPERANCE" and "MOBILE#PRICE" are two mentioned categories, and the OTE in this example is the "mobile" because user is targeting the mobile's attribute.

The sequence-labeling techniques, e.g., Conditional Random Field (CRF), have been proved effective for extracting different kind of aspects through neural-contextual word embeddings employed by deep-learning mechanism [37], [38]. Many researchers have integrated CRF and Recurrent Neural Network (RNN) to extract explicit aspects and sentiment words through learning sequential features based on likelihood and backpropagation mechanism [8], [10]. For instance, Giannakopoulos *et al.* [39] utilized BiLSTM and CRF to handle the extraction and sequential-labeling of explicit aspects and OTE, simultaneously, through continuous word representations. They achieved high precision score and performed AE in both supervised and unsupervised manner. Rana and Cheah [40] also extracted explicit aspects and OTE by generating sequential-pattern rules through CRF on the basis of direct and indirect correlation between aspect and sentiment words. They focused on learning pattern rules from users' review, instead of manually designing them, to mitigate the effect of language constraints and grammatical rules. Jebbara and Cimiano [41] proposed RNN supplemented with character-level embeddings to extract OTE after scrutinizing its characteristics through a sequence-labeling system, i.e., CRF. The inclusion of character embeddings helped to rectify the robustness of unseen words and spelling errors.

CRF has also been applied for grouping semantic, syntactic and lexical aspects according to their respective ambiguities [42], [43]. For instance, Ma *et al.* [44] discovered aspects through a hierarchical multi-layer Bidirectional Gated Recurrent Unit (BiGRU) that highlighted character features and high-level semantic features by capturing long-range dependencies between aspects and targets. The resulted features helped in estimating sentiment labels through sequence-labeling CRF.

Moreover, researchers have achieved improved aspect representations by utilizing neural-memory operations and attention encoders through memory interactions and attention mechanisms, respectively [38], [45], [46]. These two phenomena handle the interactions between aspects and sentiment words that soothe the extraction procedure, and also help to achieve the multi-task learning environment [47]. For instance, Li and Lam [45] proposed a memory-interaction mechanism with two Long Short Term Memory (LSTM) for extracting aspect and sentiment words through a multi-task-learning environment. Their memory operations were based on the positional information of aspects and sentiment words, and global score of sentiment terms. They also added the constraints of sentimental sentences to facilitate the extraction process through another LSTM. Wang *et al.* [48] proposed multi-layer neural attentions with tensor operators for handling dual-interaction between aspects and sentiment words. They guided attentions through input word embeddings and the prototype vectors of aspects and sentiment words, in order to measure the attention score for each input word, where words having high-attention scores were considered as an aspect or sentiment word. Further, Li *et al.* [49] deployed trimmed-history-attention mechanism to encode useful history-aware-aspect representation into sequential-aspect representation obtained from two-stacked LSTMs. The employment of two-stacked RNNs and afterwards an auxiliary-opinion-based-word-recognition module helped in refining the boundaries of extracted OTE. Angelidis and Lapata [50] proposed a weakly-supervised-neural-attention encoder that averaged word vectors in each segment to

TABLE 2
Reported Performance of Presented Solutions for Aspect Extraction

| Ref. | Approach Used | Evaluation Task (Extraction) | Dataset (Domain) | | Performance Precision | Recall | F1. Score |
|---|---|---|---|---|---|---|---|
| Yin et al. 2016 [37] | unsupervised | aspect | SemEval 2014 (laptop (L)) [88] | | -- | -- | 75.16 |
| | | | SemEval 2014 (restaurant (R)) [88] | | | | 84.97 |
| | | | SemEval 2015 (R) [12] | | | | 69.73 |
| Wang et al. 2016 [8] | supervised | aspect / opinion term | SemEval 2014 (R) | | -- | -- | 84.93 / 84.11 |
| | | | SemEval 2014 (L) | | | | 78.42 / 79.44 |
| Luo et al. 2019 [10] | supervised | aspect | SemEval 2014 (L) | | -- | -- | 80.57 |
| | | | SemEval 2014 (R) | | | | 84.83 |
| | | | SemEval 2015 (R) | | | | 70.83 |
| | | | SemEval 2016 (R) [89] | | | | 74.49 |
| Giannakopoulos et al. 2017 [39] | supervised | aspect | SemEval 2014 (L) | | -- | -- | 74.55 |
| | | | SemEval 2014 (R) | | -- | | 84.01 |
| | unsupervised | | SemEval 2014 (L) | | 74.51 | | 44.37 |
| | | | SemEval 2014 (R) | | 83.19 | | 63.09 |
| Al-Smadi et al. 2018 [74] | supervised | multi-lingual OTE | SemEval 2016 (hotel (H)) [89] | | -- | -- | 69.98 |
| Agerri and Rigau 2019 [43] | supervised | OTE | SemEval 2014 | | 81.15 | 87.30 | 84.11 |
| | | | SemEval 2015 | | 72.9 | 69 | 70.90 |
| | | | SemEval 2016 | | 73.33 | 73.69 | 73.51 |
| | | multi-lingual OTE | SemEval 2016 | Dutch | 75.36 | 65.22 | 69.92 |
| | | | | French | 69.94 | 69.08 | 69.50 |
| | | | | Russian | 68.27 | 64.61 | 66.39 |
| | | | | Spanish | 64.21 | 66.91 | 65.53 |
| | | | | Turkish | 62.29 | 57.93 | 60.22 |
| Rana and Cheah 2018 [40] | supervised | OTE | customer reviews [90] | | 86 | 91 | 89 |
| Ma et al. 2018 [44] | supervised | target detection | English (tweets) [91] | | 60.12 | 53.68 | 56.98 |
| | | | Spanish (tweets) [91] | | 68.64 | 63.66 | 66.01 |
| Jebbara and Cimiano 2017 [41] | supervised | OTE | SemEval 2016 (R) | | -- | -- | 65.86 |
| Wang et al. 2017 [48] | supervised | aspect / opinion term | SemEval 2014 (R) | | -- | -- | 85.29 / 83.18 |
| | | | SemEval 2014 (L) | | | | 77.80 / 80.17 |
| | | | SemEval 2015 (R) | | | | 70.73 / 73.68 |
| Li et al. 2018 [49] | supervised | aspect | SemEval 2014 (R) | | -- | -- | 85.61 |
| | | | SemEval 2014 (L) | | | | 79.52 |
| | | | SemEval 2015 (R) | | | | 71.46 |
| | | | SemEval 2016 (R) | | | | 73.61 |
| Wang et al. 2017 [47] | supervised | aspect category / opinion term | SemEval 2014 (L) | | -- | -- | 57.06 / 63.53 |
| | | | SemEval 2015 (R) | | | | 63.16 / 59.17 |
| | | | SemEval 2016 (R) | | | | 65.34 / 61.44 |
| Li and Lam 2017 [45] | supervised | aspect | SemEval 2014 (L) | | -- | -- | 77.58 |
| | | | SemEval 2016 (R) | | | | 73.44 |
| Angelidis and Lapata 2018 [50] | weakly supervised | aspect | oposum dataset (amazon reviews) | | 57.8 | -- | 49.1 |
| Gu et al. 2017 [53] | supervised | aspect-mapping | Amazon Reviews (Smartphone) | | -- | -- | 78.09 |
| | | | Taobao Reviews (Skirt) | | | | 93.12 |
| Xu et al. 2018 [54] | supervised | aspect | SemEval 2014 (L) | | -- | -- | 81.59 |
| | | | SemEval 2016 (R) | | | | 74.37 |
| Pham and Le 2018 [55] | supervised | aspect category detection | restaurant reviews | | 83.94 | 81.61 | 82.76 |
| Jangid et al. 2018 [92] | supervised | aspect | FiQA 2018 (financial tweets) | | -- | -- | 69 |
| Chatterji et al. 2017 [59] | hybrid | aspect identification | customer reviews | | 79.22 | 70.93 | 74.85 |
| Ma et al. 2018 [9] | hybrid (supervised) | aspect categorization | sentihood (yahoo querying) [93] | (Sentic) | -- | -- | 77.66 |
| | | | | (Hybrid) | | | 77.87 |
| | | | SemEval 2015 (reviews) | (Sentic) | | | 73.82 |
| | | | | (Hybrid) | | | 75 |
| Poria et al. 2016 [61] | unsupervised | aspect with categories | SemEval 2015 (R) | | 92.12 | 88.25 | -- |
| Schmitt et al. 2018 [51] | unsupervised | aspect categorization | Germeval 2017 [94] | | -- | -- | 62.3 |
| | | | German Wikipedia | | | | 61 |
| Li and Lu 2017 [11] | supervised | entity recognition | English (tweets) | -- | 66.35 | 56.59 | 61.08 |
| | | | Spanish (tweets) | -- | 73.13 | 64.34 | 68.45 |
| Wu et al. 2018 [65] | hybrid (unsupervised) | aspect | SemEval 2014 (R) | | 72.81 | 79.81 | 76.15 |
| | | | SemEval 2014 (L) | | 55.91 | 66.51 | 60.75 |
| | | OTE | SemEval 2015 | | 62.26 | 65.13 | 63.36 |
| | | | SemEval 2016 | | 58.94 | 70.59 | 64.24 |
| | | cross-domain OTE | SemEval 2015 (H) | | 55.86 | 84.58 | 67.27 |
| Marcacini et al. 2018 [71] | semi-supervised | cross-domain OTE | product reviews [90] | | -- | -- | 60 |
| | | | SemEval 2014 (R) | | | | 68.3 |
| | | | SemEval 2014 (L) | | | | 61 |
| Shu et al. 2017 [72] | supervised | cross-domain aspect / in-domain aspect | customer reviews [90], [82] | | 82.5 / 84.3 | 53.1 / 71.4 | 64.3 / 77.3 |
| Gaillat et al. 2018 [60] | supervised | aspect | stock trading | | 56.89 (Accuracy) | | |
| Akhtar et al. 2017 [64] | unsupervised | aspect | SemEval 2014 (R) | | 87.09 | 82.10 | 84.52 |
| | | | SemEval 2014 (L) | | 85.49 | 66.7 | 74.93 |
| Jebbara and Cimiano 2019 [77] | unsupervised | cross-lingual OTE | SemEval 2016 | Dutch | -- | -- | 66.00 |
| | | | | English | | | 68.70 |
| | | | | Russian | | | 62.40 |
| | | | | Spanish | | | 56.70 |
| | | | | Turkish | | | 49.00 |
| Souchen et al. 2017 [87] | supervised | aspect category | SemEval 2014 (R) | | 84.4 | 83.1 | 83.8 |
| | unsupervised | | | | 69.5 | 64.7 | 67.0 |
| He et al. 2017 [46] | unsupervised | aspect | restaurant reviews [95] | | 85.66 | 72.23 | 77.50 |
| | | | BeerAdvocate (reviews) [96] | | 65.4 | 82.8 | 72.5 |
| Luo et al. 2018 [97] | unsupervised | prominent aspect | TripAdvisor (hotel reviews) [98] | | 70 (soft accuracy) | | |
| | | | Amazon (product reviews) [98] | | 59.75 (soft accuracy) | | |
| | | | Yelp (restaurant reviews) [98] | | 72 (soft accuracy) | | |
| Ye et al. 2017 [99] | supervised | aspect | SemEval 2014 (R) | | -- | -- | 83.97 |
| | | | SemEval 2014 (L) | | | | 75.66 |
| Schouten et al. 2017 [100] | supervised | aspect detection | SemEval 2015 | | -- | -- | 62.8 |
| Asghar et al. 2017 [101] | hybrid | aspect | customer reviews | | 83.46 | 71.0 | 77.16 |
| Konjengbam et al. 2018 [102] | unsupervised | aspect | product reviews[90] | (SemR) | 56 | 73.68 | 63.63 |
| | | | | (SemS) | 78.94 | 78.94 | 78.94 |

identify aspect words. The encoder worked on assumption that every aspect present in the data contained a small set of seed words that could be used to identify segments containing aspects through a multi-task objective.

Though, as discussed previously; RNNs (LSTMs) have been mostly used for carrying out the AE procedure. But, to deal with the semantic and syntactic irregularities, mostly present in the user-generated social media text, Convolutional Neural Network (CNN) is proved more effective than RNN [51]. Because CNN extracts local and position-invariant aspects whereas RNN captures long-range-semantic dependencies based on sequential information for classification [52]. For instance, Gu *et al.* [53] proposed cascaded-CNN structure for mapping the local semantic of each aspect through convolutional and max-pooling operations, which associated each aspect to its corresponding sentence for producing aspect category labels. Xu *et al.* [54] adjusted aspects of seen words along with its semantics for modeling label dependencies through a less complicated neural architecture. They utilized Dual-Embeddings CNN, i.e., cross-domain embeddings and domain-specific embeddings to encode the information of each input word and to achieve the AE procedure with less supervision, but they did not consider the semantics of conjunction words. Moreover, Pham and Le [55] captured more semantics in the text through three different representations of word embeddings, i.e., Word2Vec, Glove embeddings and one-hot character vec-tors. Each embedding was passed to an independent CNN channel and a non-linear activation function to produce global-sentence representations, followed by a single NN to carry out aspect-category-label-prediction task.

### 3.1.2 Implicit Aspects Extraction

Implicit and explicit aspects should be given same importance considering their relevance to the customers' reviews. Where, an implicit aspect means that it is not clearly stated in the text, e.g., "I could not use the camera because of very low charging" is an example of implicit aspect, i.e., battery, of an entity, i.e., camera. Unfortunately, explicit aspects have earned more attention of researchers relative to implicit aspects [56]. Because, the identification of implicit aspects is a challenging task as they often do not contain any name or clue words. But with the immense achievement of NNs like LSTM that are excellent in learning implicit knowledge from data through gated mechanism because they work similar to human brain and encode the importance of each word present in the text. For instance, Sentic-LSTM (an extension of LSTM) proposed by Ma *et al.* [9] offered a solution for explicitly combining the implicit and explicit knowledge. The Sentic-LSTM adopted a sequence-encoder and a self-attention mechanism to calculate and incorporate affective-common-sense knowledge into a deep-neural-sequential model for handling the significance of multi-instances target.

Other studies are also classified based on supervised, unsupervised, hybrid and semi-supervised learning for categorizing implicit aspects through dependency parsing, association rule mining, semantic ontology, classification, clustering and rule-based approach [57]. SemEval 2015 involved the segregation of implicit attributes for entities [12]. Implicit aspect indicators were also identified through a probabilistic-graphical framework, i.e., CRF for extracting implicit aspects [58]. Moreover, Chatteri *et al.* [59] used AspectFrameNet, where they considered aspects as Frame elements, for identifying implicit-aspect and explicit-aspect patterns as a sequence-labeling task (CRF). According to defined pattern rules, the AspectFrameNet updated itself with aspects' patterns for every next iteration. Gaillat *et al.* [60] classified both explicit and implicit aspects by utilizing pre-defined aspect categories in financial domain. The semantic relatedness of every input word was calculated with aspect-class label based on their occurrence, which was further provided to machine-learning algorithm for final classification. However, Poria *et al.* [61] extracted implicit aspect through Sentic Latent Dirichlet Algorithm (SLDA) that integrated common-sense reasoning in computation of word distributions. The clusters were formed by SLDA after capturing semantic association between words and multi-word expressions. The words having highest probability among clusters were considered as aspect terms.

Despite of discussed solutions, implicit-aspect extraction still remains an issue which could be handled with improved feature engineering and large datasets.

### 3.1.3 Aspects Extraction With Neutral Sentiment

Every aspect plays an integral role for improving sentiment classification accuracy. But, researchers mainly focused on aspects with positive and negative sentiments, and aspects with neutral or linguistic sentiments have been neglected [62]. At the same time, some researchers also performed proper encoding of text for detecting aspects with positive, negative and neutral sentiments, after correspondingly performing end-to-end optimization through a suitable NN [63], [64], [51]. For instance, Wu *et al.* [65] came up with a chunk-level-extraction method for extracting neutral and implicit aspects. The method contained both rule-based and supervised-learning approaches to produce rational predictions and to achieve higher-level aspect representati-ons through a deep NN architecture. Moreover, Li *et al.* [11] investigated the sentiment scope of neutral aspects through sentiment-scope graphs that captured the boundless long-distance dependencies between aspects and entities.

### 3.1.4 Cross-Domain and Cross-Lingual AE

The limitations and characteristics of domain application contribute towards domain dependence, which is a big challenge in AE [66]. Inductive-transfer learning could be used to extract common aspects (linguistic) from two domains, only if they share a common feature space and same distribution characteristics [67], [68]. The use of pre-training and fine-tuning across different domains may cause inconsistency issues because different domains have different marginal-probability distribution and feature spaces [69]. Although, cross-domain-transfer learning have reported feasible solutions, but they make the regular labeling of data, expensive or nearly impossible [6], [62], [68], [67]. On the contrary, transductive learning has been proved effective for handling the issue of classifying unlabeled data [70]. For instance, Marcacini *et al.* [71] utilized transductive learning to incorporate knowledge from different domains through a unified representation model. They mapped different features (as nodes) in a heterogeneous network, i.e., linguistic features, from labeled aspects of the source domain to unlabeled aspects of the target domain, with the help of a mathematical-formalization framework and theoretic guarantees of convergence. Shu *et al.* [72] claimed that lifelong-machine-learning CRF could be significantly improved for extracting aspects from different domains by retaining knowledge from previous domains, to facilitate future learning. Akhtar *et al.* [64] worked on an efficient Particle Swarm Optimization technique that automatically discovered the most relevant aspects, irrespective of the domain adaptation.

Commonly, the research focuses on English language [73], but other languages also gained interest in recent years [11], [74]. The use of machine translation for multi-lingual-OTE extraction requires NLP resources to perform word alignment between POS tags and dependency features [75]. Similarly, the CRF system using different features such as POS, bigrams and lemmas obtained good results for Spanish and English [76]. Agerri and Rigau [43] also modelled multi-lingual-OTE extraction as a sequence-labeling task. Their language-independent model obtained different feature's clusters, i.e., local, shallow and independent features, from diverse data sources based on semantic distribution. Jebbara and Cimiano [77] employed zero-shot-cross-lingual approach with multi-lingual word embeddings for predicting OTE. They used common vector space to transfer learning model from source language to target language.

## 3.2 Map Relationships

The explicit representations of the extracted data objects are essential to precisely map relationships between particular entities and aspects. These relationships include co-occurrence relations [78], dependency relations [79], dependency-context information [37] and other relations [80], [81], [82], which could be mapped through hierarchical representation of aspects based on tree structure, sentiment ontology or conceptual ontology. All these mapping representations help to understand the relations between different data objects and present product information in a structured way [83], [84], [85].

### 3.2.1 Co-Occurrence Relation

The co-occurrence relations help to predict complete, coherent and consistent knowledge between distribution of words, e.g., beef, mutton, fish (aspect terms), into one aspect "meat" or it can be "food". Many existing models do not incorporate the prior knowledge, e.g., consideration of topic distribution in each document, and encoding of word co-occurrence statistics to preserve topic consistency, for AE procedure, and thus they often deduced aspects of poor quality [78], [86]. To handle the issue, Souchen *et al.* [87] adopted a supervised approach for computing co- occurrence frequencies between annotated categories and lemmas. They also appended grammatical dependencies between words for more accurate aspect- category (implicit and explicit) detection. Moreover, they also considered word co-occurrence frequencies for computing direct and indirect relations between words through association-rule mining in an unsupervised manner. They assigned activation value to each word through spreading-activation process, where the word having higher activation value was considered as an aspect category. He *et al.* [46] mapped the co-occurrence between words according to their context for discovering coherent aspects in the neural-embedding space. They successfully understated non-aspect words through attention mechanism and thus maintained the uniqueness of word embeddings. Li and Lam [45] also captured the co-occurrence patterns between aspects and sentiment words through memory interactions. The neural-memory operators were designed to achieve interactions between data objects and to generate task-level information summary.

The co-occurrence relations between words could also be captured through association-rule-mining techniques [103], aspects-clustering [104], co-occurrence matrix [105] and graph-based methods [106]. Where, co-occurrence matrix focuses on relations between sentences and aspects with the intention of finding implicit aspects as well, and graph-based methods utilize probabilistic models to define edges' weights as co-occurrence relation between words.

But sometimes, the identification of co-occurrence relations and word-frequency information leads to the extraction of similar aspects from sentences, but in actual scenario these aspects should be considered differently. For example, "beautiful design" and "good looks" should be two different aspects of mobile phone, although both come under the category of "appearance". To address this issue, Luo *et al.* [97] addressed the overlapping problem of potential aspect terms through lexico-syntactic examination of input data. They found unique aspect terms at subsumed relations in the subgraph through synsets in WordNet. Their method covered both prominent and distinct aspects adequately.

### 3.2.2 Semantic and Dependency Relation (Hierarchical and Ontology Structure)

Dependency patterns based on semantic and syntactic sequences help to discover the missing synonymous aspects and also distinguish the non-aspect words [82], [73]. These dependency relations could be achieved either through a hierarchical structure or an ontology tree.

The hierarchical structure helps to achieve the distributed representation learning by performing the relational classification between two aspects (nodes); where nodes can be adjacent nodes or parent and child nodes [8]. The tree dependency information of sentences proposed by Ye *et al.* [99] captured the syntactic and linguistic aspects through convolutional-stacked NN. Further, they incorporated an inference layer to achieve final tag scores. Moreover, Yin *et al.* [37] encoded neural embeddings with syntactic and contextual information to explicitly learn the semantic embedding paths as grammatical relations in dependency tree through recurrent NN, and utilized sequence-labeling CRF for improved AE. Similarly, Luo *et al.* [10] also structured the sequence-labeling syntactic-dependency tree based on bidirectional-gated mechanism through BiLSTM for AE.

The use of ontology tree and ontology feature as a knowledge-base help to define the relationships between different domain-concepts. These axioms can derive implicit stated information to generate aspects and review summaries for improved extraction performance, and also encode domain-knowledge into an ontology tree to reduce the need of training data [107]. For instance, Schouten *et al.* [100] encoded domain-knowledge into an ontology tree enriched with target and sentiment lexicons for handling the task of aspect detection as binary-classification. The association of text to its domain-concept led to strong indication for aspect detection. Konjengbam *et al.* [102] formed a hierarchical-tree structure that included aspects, sub-aspects, their relations and the semantic relationships of various aspects. They created two ontology trees based on semantic relationship and semantic-similarity relationship to incorporate every product related information after exploring all the aspects and their related review-snippet.

Besides hierarchical structure and ontology tree, heuristic patterns based on semantic-similarity also produce a reasonable approximate solution towards AE in a reasonable time [108]. For instance, Asghar *et al.* [101] composed a hybrid-integrated framework with an extended set of heuristic patterns, where noun, noun-phrases (multi-words) and verbs were considered as candidate terms from the review data, to extract aspects those were grouped by the semantic-similarity measure.

## 4 Aspect Sentiment Analysis (ASA)

ASA, the second phase of AbSA, assigns the sentiment score to each extracted aspect, target, or entity. It also includes the interactions, dependencies and contextual-semantic relationships between different data objects to enhance the sentiment classification accuracy. All solutions featuring ASA are presented in this section and Table 3.

### 4.1 Sentiment Analysis (SA)

ASA provides more detailed information than general SA, because it predicts the sentiment polarity of the given aspects, targets and entities present in the text. Initially, ASA was handled by manually designing features, such as n-grams, sentiment lexicons or dependency information [109], [110]. But, with the progression of deep-learning mechanisms, ASA approaches have been projecting for automatically learning of aspects and their sentiments, providing best solutions to many problems in AbSA [111], [112].

#### *4.1.1 Aspect (Target)-Level SA*

Aspect (target)-level SA classifies sentiments by learning separate representation for each data object. NN models get clear representation of words, i.e., adding more information at the word-level, by measuring and identifying the semantic and syntactic relatedness between different data objects [51], [113]. The implementation of BiLSTM with character-level embeddings have performed clear representation of OTE and non-vocabulary words, and thus contributed in the acquisition of good sentiment information [74]. For instance, Ma *et al.* [44] learned and pointed out non-vocabulary words through a hierarchical multi-layer BiGRU. The model produced target labels appropriately and thus made good prediction for sentiment labels. Pham *et al.* [114] combined feed-forward NN, containing representation learning techniques of word embeddings, with compositional vector model for capturing semantic-information and richer-knowledge representations. The designed NN utilized existing aspect-ratings and higher-aspect representation layer to produce compositional sentiments. Ghasedi and Huang [115] adopted a CrowdDeep autoencoder coupled with probabilistic approach for efficiently reconstructing and reducing the noise of corrupted-text data. The approach accurately categorized sentiments by estimating the underlying information of text data. It also did not encounter any memory exhaustion problem during handling insufficient training parameters in very large datasets because of utilizing text data as a source of information. Besides NN, Asghar *et al.* [101] composed a hybrid-integrated framework to group extracted aspects according to their semantic-similarity. The sentiment scores were assigned to aspects through a sentiment-scoring technique based on lexicon-based and corpus-based concepts.

Besides sequential models like LSTM and GRU, CNN is also proved effective for achieving targeted sentiment classification accuracy [73], [116] along with many other NLP tasks such as relation classification [56] and information retrieval [117]. For instance, Xue and Li [118] developed a gated-convolutional network, containing novel gated Tanh-ReLU units (GTRU), that utilized aspect embeddings for selecting n-gram features on each receptive field to perform aspect-category SA and aspect-term SA. The GTRU units via ReLU activation function, on the top of the convolutional layers, made the network suitable for parallel computing that contributed towards reduced training time. Moreover, Zhao *et al.* [119] proposed CNN-based-weakly-supervised-deep embeddings for learning high-level representations that reflected general sentiment distribution of sentences from a large number of weakly-labeled sentences. They utilized review ratings, as weak labels, and labelled sentences for training and fine-tuning deep NN, respectively. In addition, Pham and Le [55] employed a multiple-CNN model, where every CNN was initialized with a different word embedding, i.e., Word2Vec, Glove and one-hot character embeddings, for capturing semantics in the text. Each CNN module was trained with the same non-linear activation function, simultaneously. The final vector representations were produced through a single NN for classifying sentiments. Li *et al.* [120] utilized CNN layer for extracting salient features from the transformed word representations originated from a bidirectional RNN. They adopted a proximity strategy that accurately located the sentiment indicators by scaling the input of CNN layer with positional relevance between word and target. The technique demonstrated its capability by handling both general and target-sensitive sentiment.

Although, RNN and CNN both significantly process out relevant information from one step to another through gated mechanisms and convolutional procedures for improved sentiment classification. But with the longer-input sequences, sometimes it becomes difficult for a NN to keep the context of hidden vectors. Here, attention mechanism helps to mitigate long-sequence issue by encoding the most relevant information of the input sequences. It combines with neural word embeddings to capture the key parts of the sentence, which helps to explicitly combine the explicit and implicit knowledge and produces good sentiment information [9], [63], [113]. For instance, He *et al.* [121] utilized attention-based LSTM that was trained on aspect-level data for capturing domain-specific sentiment words. They hypothesized that domain-knowledge could be fully exploited to achieve additional knowledge from documents, that were from similar domain, by using two transfer-learning methods, i.e., pre-training [122] and multi-task learning [56], [123], as these two tasks are highly related semantically. Moreover, Hu *et al.* [124] utilized aggregated-sentiments and negation-specific words as attentions for capturing the semantic components

TABLE 3
Reported Performance of Presented Solutions for Aspect Sentiment Analysis (ASA)

| Ref. | Approach | Evaluation Task (ASA) | Dataset (Domain) | | Performance | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Accuracy | Precision | Recall | F1. Score |
| Al-Smadi et al. 2018 [74] | supervised | aspect | SemEval 2016 (H) | | 82.6 | -- | -- | -- |
| Ma et al. 2018 [44] | supervised | target | English (tweets) | | -- | 46.52 | 39.99 | 42.87 |
| | | | Spanish (tweets) | | | 48.09 | 43.44 | 45.61 |
| Ma et al. 2018 [9] | hybrid (supervised) | targeted aspect | sentihood (yahoo querying) [93] | (Sentic) | 89.32 | -- | -- | -- |
| | | | | (Hybrid) | 87.78 | | | |
| | | | SemEval 2015 (reviews) | (Sentic) | 76.47 | | | |
| | | | | (Hybrid) | 74.11 | | | |
| Li et al. 2018 [147] | supervised | multi-aspect | TripAdvisor (TripOUR) [139] | | 60.70 | -- | -- | -- |
| | | | TripAdvisor (TripDMS) [139] | | 48.21 | | | |
| Schmitt et al. 2018 [51] | unsupervised | aspect | Germeval 2017 [94] | | -- | -- | -- | 51.1 |
| | | | German Wikipedia | | | | | 50.2 |
| Gu et al. 2017 [53] | supervised | aspect | Amazon Reviews (Smartphone) | | 84.87 | -- | -- | -- |
| | | | Taobao Reviews (Skirt) | | 98.26 | | | |
| Huang and Carley 2018 [116] | supervised | aspect | SemEval 2014 (L) | (PF-CNN) | 70.06 | -- | -- | -- |
| | | | | (PG-CNN) | 69.12 | | | |
| | | | SemEval 2014 (R) | (PF-CNN) | 79.20 | | | |
| | | | | (PG-CNN) | 78.93 | | | |
| Xue and Li 2018 [118] | supervised | aspect target | SemEval 2014 (L) | | 69.14 | -- | -- | -- |
| | | | SemEval 2014 (R) | | 77.28 | | | |
| Zhao et al. 2018 [119] | weakly supervised | aspect | Amazon Reviews [148] | CNN | 87.7 | -- | -- | 87.6 |
| | | | | LSTM | 87.9 | | | 87.9 |
| Pham and Le 2018 [55] | supervised | aspect | restaurant reviews | | -- | -- | -- | 84.16 |
| Ghasedi and Huang 2018 [115] | hybrid | target | CrowdFlower dataset | | 91.2 | -- | 82.5 | -- |
| | | | Sentiment Polarity dataset [149] | | 91.5 | | 91.5 | |
| Angelidis and Lapata 2018 [50] | weakly-supervised | opinion summarization | oposum dataset (amazon reviews) | | 44.1 (ROUGE-1) | | | |
| Pham et al. 2018 [114] | supervised | aspect rating | TripAdvisor [150] | | *(Δaspect) 59.6* | -- | -- | -- |
| Hu et al. 2018 [124] | unsupervised | word negation | Yelp 2013 | | 64.9 | -- | -- | -- |
| | | | Yelp 2014 | | 67.2 | | | |
| | | | Yelp 2015 | | 70.4 | | | |
| | | | IMDB | | 53.5 | | | |
| He et al. 2018 [121] | supervised | aspect | SemEval 2014 (L) | | 71.15 | -- | -- | 67.46 |
| | | | SemEval 2014 (R) | | 79.11 | | | 69.73 |
| | | | SemEval-2015 (R) | | 81.30 | | | 68.74 |
| | | | SemEval-2016 (R) | | 85.58 | | | 69.76 |
| Tang et al. 2016 [128] | supervised | aspect | SemEval 2014 (L) | | -- | -- | -- | 72.21 |
| | | | SemEval 2014 (R) | | | | | 80.95 |
| Tay et al. 2017 [14] | supervised | aspect target | SemEval 2014 (L) | (CORR) | 64.89 | -- | -- | -- |
| | | | | (CONV) | 68.81 | | | |
| | | | SemEval 2014 (R) | (CORR) | 74.76 | | | |
| | | | | (CONV) | 75.44 | | | |
| | | aspect category | SemEval-2015 (R) | (CORR) | 80.47 | | | |
| | | | | (CONV) | 81.29 | | | |
| | | | SemEval-14+15 | (CORR) | 74.68 | | | |
| | | | | (CONV) | 78.44 | | | |
| Zhu and Qian 2018 [129] | supervised | target | SemEval 2014 (L) | | 74.45 | 72.96 | 69.21 | 70.16 |
| | | | SemEval 2014 (R) | | 82.32 | 74.68 | 70.18 | 71.45 |
| | | aspect term | SemEval 2014 (R) | | 86.33 | 77.54 | 73.82 | 75.16 |
| | | | SemEval 2016 (tweets) | | 72.14 | 64.52 | 58.96 | 60.24 |
| Asghar et al. 2017 [101] | hybrid | aspect | customer reviews | | -- | 85 | 73 | 78 |
| Li and Lu 2017 [11] | supervised | entity | English (tweets) | | -- | 47.3 | 40.36 | 43.55 |
| | | | Spanish (tweets) | | | 47.14 | 41.48 | 44.13 |
| Yang et al. 2018 [13] | supervised | multi-entity aspect | baby care (BC) dataset | | 80.74 | 86.42 | 84.28 | 85.34 |
| Yang et al. 2017 [140] | supervised | target entity | Tweets | (ABLSTM1) | 71.6 | -- | -- | 71.2 |
| | | | | (ABLSTM2) | 72.6 | | | 72.2 |
| Chen et al. 2017 [133] | supervised | aspect | SemEval 2014 (L) | | 74.49 | -- | -- | 71.35 |
| | | | SemEval 2014 (R) | | 80.23 | | | 70.80 |
| | | | Tweets | | 69.36 | | | 67.30 |
| | | | Chinese news comments | | 73.89 | | | 73.85 |
| Zheng and Xia 2018 [132] | supervised | aspect | SemEval 2014 (L) | | 75.24 | -- | -- | -- |
| | | | SemEval 2014 (R) | | 81.34 | | | |
| | | | Tweets | | 72.69 | | | |
| Yang et al. 2018 [151] | supervised | target dependent | Tweets | | 71.2 | -- | -- | 68.8 |
| | | | Sina Weibo Dataset (Chinese) | | 69.8 | -- | -- | 68.4 |
| Fan et al. 2018 [134] | supervised | multi-word aspect | SemEval 2014 (L) | | 76.37 | -- | -- | 72.10 |
| | | | SemEval 2014 (R) | | 78.26 | | | 68.38 |
| | | | Tweets | | 72.11 | | | 70.8 |
| He et al. 2018 [125] | unsupervised | aspect | SemEval 2014 (L) | | 71.94 | -- | -- | 69.23 |
| | | | SemEval 2014 (R) | | 80.63 | | | 71.32 |
| | | | SemEval 2015 (R) | | 81.67 | | | 66.05 |
| | | | SemEval 2016 (R) | | 84.61 | | | 67.45 |
| Balikas et al. 2017 [137] | unsupervised | fine grained feature | SemEval 2016 (R) | | -- | -- | -- | 48.1 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Li et al. 2017 [138] | supervised | aspect | Debates | | 78.48 | 74.55 | 66.31 | 67.68 |
| | | | SemEval 2016 (tweets) | | 74.76 | 68.40 | 62.09 | 64.62 |
| | | | SemEval 14 + 15 (reviews) | | 65.58 | 50.34 | 44.95 | 45.93 |
| Yin et al. 2017 [139] | supervised | multi-aspect | TripAdvisor [150] | | 46.65 | -- | -- | -- |
| | | | BeerAdvocate [96] | | 38.25 | | | |
| Tay et al. 2017 [127] | supervised | aspect term | SemEval 2014 (L) | (Tensor) | -- | 58.08 | 56.60 | 55.24 |
| | | | | (Holo) | | 60.15 | 60.20 | 60.11 |
| | | | SemEval 2014 (R) | (Tensor) | | 60.71 | 57.24 | 58.61 |
| | | | | (Holo) | | 62.05 | 57.82 | 58.82 |
| | | aspect category | SemEval 2014 (R) | (Tensor) | | 68.73 | 65.17 | 66.64 |
| | | | | (Holo) | | 66.29 | 62.43 | 63.99 |
| | | | Reviews [12], [88] | (Tensor) | | 59.06 | 59.81 | 58.59 |
| | | | | (Holo) | | 55.34 | 56.56 | 55 |
| | | | SemEval 2016 (tweets) | (Tensor) | | 72.11 | 72.79 | 72.42 |
| | | | | (Holo) | | 71.07 | 71.38 | 71.24 |
| | | | Debates (Web forums) | (Tensor) | | 66.53 | 66.07 | 66.17 |
| | | | | (Holo) | | 63.59 | 63.27 | 63.34 |
| Liu et al. 2018 [141] | supervised | aspect | SemEval 2014 (L) | | 75.07 | -- | -- | -- |
| | | | SemEval 2014 (R) | | 80.89 | | | |
| | | | Tweets | | 71.53 | | | |
| Gu et al. 2018 [142] | supervised | aspect | SemEval 2014 (L) | | 74.12 | -- | -- | -- |
| | | | SemEval 2014 (R) | | 81.16 | | | |
| Majumder et al. 2018 [143] | supervised | aspect | SemEval 2014 (L) | | 73.8 | -- | -- | -- |
| | | | SemEval 2014 (R) | | 80 | | | |
| Wang et al. 2018 [15] | supervised | aspect | SemEval-2015 (L) | | 81.6 | -- | -- | 66.7 |
| | | | SemEval-2015 (R) | | 80.9 | | | 68.5 |
| Wang and Lu 2018 [144] | supervised | aspect | SemEval 2014 (L) | | 75.1 | -- | -- | -- |
| | | | SemEval 2014 (R) | | 81.6 | | | |
| | | | Tweets | | 69 | | | |
| | | cross-domain aspect | SemEval 2015 (R) | English | 88.7 | | | |
| | | | | Spanish | 88 | | | |
| | | | | French | 82.4 | | | |
| | | | | Turkish | 83.7 | | | |
| | | | | Russian | 82.8 | | | |
| | | | | Dutch | 87.3 | | | |
| | | | SemEval 2015 (H) | Arabic | 86.9 | | | |
| Hazarika et al. 2018 [145] | supervised | inter-aspect dependencies | SemEval 2014 (L) | | 79.0 | -- | -- | -- |
| | | | SemEval 2014 (R) | | 72.5 | | | |
| Lin et al. 2019 [146] | supervised | inter-aspect dependencies | SemEval 2014 (L) | | 77.59 | -- | -- | 81.16 |
| | | | SemEval 2014 (R) | | 73.61 | | | 71.50 |
| Liu and Zhang 2017 [131] | supervised | target | T-Dataset [113] | | 73.6 | -- | -- | 72.1 |
| | | | Z-Dataset [152] | | 75 | | | 72.3 |
| Wang et al. 2018 [153] | supervised | aspect/target | SemEval 2014 (L) | (NP) | -- | -- | -- | 72.43 |
| | | | | (CNP) | | | | 70.25 |
| | | | | (IT) | | | | 71.37 |
| | | | | (CI) | | | | 71.67 |
| | | | | (JCI) | | | | 71.79 |
| | | | | (JPI) | | | | 70.18 |
| | | | SemEval 2014 (R) | (NP) | | | | 75.73 |
| | | | | (CNP) | | | | 76.65 |
| | | | | (IT) | | | | 78.55 |
| | | | | (CI) | | | | 78.69 |
| | | | | (JCI) | | | | 78.79 |
| | | | | (JPI) | | | | 77.95 |
| Ma et al. 2017 [154] | supervised | aspect | SemEval 2014 (L) | | 72.1 | -- | -- | -- |
| | | | SemEval 2014 (R) | | 78.6 | | | |
| Ma et al. 2019 [155] | supervised | multi-aspect | SemEval 2014 (L) | | 73.1 | -- | -- | -- |
| | | | SemEval 2014 (R) | | 80.1 | | | |
| Fan et al. 2018 [156] | supervised | aspect | SemEval 2014 (L) | | 75.39 | -- | -- | 72.47 |
| | | | SemEval 2014 (R) | | 81.25 | | | 71.94 |
| | | | Tweets | | 72.54 | | | 70.81 |
| Ma et al. 2017[157] | supervised | aspect | SemEval 2014 (L) | | 72.68 | -- | -- | -- |
| | | | SemEval 2014 (R) | | 82.03 | | | |
| Li et al. 2018 [120] | supervised | target | SemEval 2014 (L) | (TNet-LF) | 76.01 | -- | -- | 71.47 |
| | | | | (TNet-AS) | 76.54 | | | 71.75 |
| | | | SemEval 2014 (R) | (TNet-LF) | 80.79 | -- | -- | 70.84 |
| | | | | (TNet-AS) | 80.69 | | | 71.27 |
| | | | Tweets | (TNet-LF) | 74.68 | -- | -- | 73.36 |
| | | | | (TNet-AS) | 74.97 | -- | -- | 73.60 |
| Qiu et al. 2018 [158] | supervised | aspect | yelp (reviews) | | 82.90 | -- | -- | -- |

from data to form sentence representations. Next, they incorporated the hierarchical structure of word, sentence and document representations into one-target-class label for final sentiment prediction. He *et al.* [125] adopted an autoencoder trained with a neural-attention-based sentiment classifier for learning aspect embeddings those were semantically related (meaningful). Further, they exploited a local-attention mechanism to create a weighted combination of aspect embeddings for a given target by averaging the target and context information. The adopted autoencoder provided good target representation with a high accuracy on the predicted sentiment. Angelidis and Lapata [50] utilized a hierarchical-attention-based-neural architecture that adopted a greedy algorithm for discarding redundant opinions. The neural architecture required little knowledge and less supervision for sentiment classification, and for generating well-balanced opinion-based summary from high-ranked opinions with minimal human intervention.

Another category of network architectures are memory networks that provide an explicit context representation for every input word in the sequence [126]. Memory networks, like attention mechanisms, also mitigate the issue of learning long-range dependencies in sequential data, and draw relationships between different data objects for improved sentiment performance [14], [127]. For instance, Tang *et al.* [128] employed a multi-layers external memory, where each layer acted as an attention mechanism, for learning significance of each context word. They considered aspect terms as a query and utilized contextual information for continuous text representation. The computed features of last layer were considered for sentiment classification. Moreover, Zhu and Qian [129] performed the interactions between two memories, i.e., deep memory and auxiliary memory, for learning the context of each input word and for explicitly generating connections between aspects and terms. They considered each memory as attention, and the result of auxiliary memory was fed to the main memory for final sentiment classification.

#### 4.1.2 Entity-Level SA

Entity SA is considered as a subdomain of ASA. Sentiment-scope graphs were introduced to jointly determine the named entities and their respective sentiments based on assumption that each entity is surrounded by an unbounded window that is responsible for capturing its sentiment polarity, which could not be achieved by fixed window of bounded size [11], [130]. But sometimes, reviews contain entities those share same aspects and it becomes difficult to capture sentiment dependencies between aspects and entities. For example, "Bought Johnsons baby lotion, texture was very smooth, but bit expensive. Then I tried Mother Care but texture was bit oily". This example contains two aspects, i.e., price and texture, that are shared by two entities, i.e., Johnsons and Mother Care. Addressing the problem, Yang *et al.* [13] modelled the context, entity and aspect memory, simultaneously. Where, context memory utilized three layers, i.e., interaction, position and LSTM layer, for performing element-wise multiplication and concatenation of entity, aspect and context information. The other two memories, i.e., entity and aspect memory, effectively updated context memory in an iterative manner for predicting the sentiment polarity towards each pair, i.e., aspect-entity pair, present in the data.

#### 4.1.3 Multi-Word Target SA

Reviews on social data mostly contain aspects with more than one word, e.g., hot-dog, mango pudding, Chinatown etc. Single-attention-based methods or merely LSTMs are not suitable for multi-word expressions, because they performed aspect-mapping by taking the average of word vectors that worked well for single word targets, but could not fully capture the semantics of multi-word targets [121], [111]. In this way, they also might disturb the integrity of each attended word [63]. Therefore, studies have been designed for modeling the contribution (context) of each word (multi-word) present in the sentence through attention mechanisms and RNN architectures [131], [132]. For instance, Chen *et al.* [133] utilized multiple attentions (memory) that were non-linearly combined with the help of BiLSTM for handling complicated multi-word expressions. Every target in a sentence possessed its own suitable memory and the weight of memory slices were defined according to the position of target in a particular sentence. However, Fan *et al.* [134] proposed a convolutional-based memory network incorporated with an attention mechanism for explicitly modeling both words and multi-words information in the sentence. The model mapped low-dimensional embedding space, extracted sequential aspects, and captured long-distance dependencies by storing context information into a fixed-size window through BiGRU for sentiment classification.

#### 4.1.4 Multi-Task Learning SA

Traditional SA approaches have separately handled the task of ternary (3-category) and fine-grained (5-category) classification learning. But with the passage of time, multi-task learning has been potentially validating in various domains through different data-learning techniques [56], [123], [135]. These techniques elegantly access resources which are developed for similar tasks to learn hidden representation of different tasks and to promote multi-task learning environment through NNs [136], [47]. For instance, Balikas *et al.* [137] performed ternary and fine-grained sentiment classification to jointly learn multiple independent tasks through BiLSTM. The tasks were correlated by sharing information, which was expected to improve the overall generalization ability. Each task was assigned to an independent softmax layer for final classification. Moreover, Li *et al.* [138] adopted a multi-task deep memory network for effectively modeling the interactions between subtasks and targets through sharing a common semantic-space. The semantic-similarity helped to simultaneously learn the targets and their respective sentiment polarities. Furthermore, Yin *et al.* [139] modelled a hierarchical-attention architecture, as a machine comprehension problem, with multi-task framework for building different representations at both word-level and sentence-level for ASA. These representations interacted with aspect-questions, where pseudo question-answer pairs were constructed by utilizing some aspect-related keywords and ratings, for learning aspect-aware-document representation through input-encoders and iterative-attention modules.

### 4.2 Interactions and Contextual Sentiment Information for Improved ASA

#### 4.2.1 Interaction Between Data Objects

Interactions and dependencies between data objects achieve refined and accurate aspects' representations, and sentiment classification. But some existing works do not consider the neighboring aspects and inter-aspect relationships or dependencies in a sentence [113], [140]. Single NNs also lack the representation learning capability for capturing relevance between aspects and terms, and for drawing relationships between different aspects, and between aspects and word terms [126], [128]. However, the utilization of attention mechanisms and deep memory networks have been proving effective for drawing relationships between different data objects by focusing on the corrected aspect terms and by capturing long-distance, inter-aspect, clause-level and structural dependencies from the sentences. For instance, Tay *et al.* [14] adopted circular convolution and circular correlation of vectors for modeling relationship between aspects and words through an attention layer. The attention calculated the probabilistic weights of aspect-word fusion by utilizing an associative-memory operator. These learned attention scores and all the hidden representations of the LSTM layer were then passed to the softmax for final sentiment classification. The model was efficient and inexpensive, as it did not append any extra tasks on LSTM for learning word-aspect relationship. Liu *et al.* [141] also considered the correlations between words and aspects through a content-attention mechanism. They first captured the important information about a given aspect from a global perspective through a sentence-level-content-attention mechanism. Next, to correlate aspects and words, and to embed the sequential words into customized memories, they employed a context-attention mechanism. Both attentions mutually considered the whole meaning of the sentence conveyed by each word (aspect) for final sentiment classification. Moreover, Tay *et al.* [127] adopted memory networks that utilized parameterized-neural-tensor compositions and holographic compositions for modeling richer interactions between aspects and words. The rich-dyadic interactions skilled with complex-valued computations helped to achieve improved sentiment classification performance. Zhu and Qian [129] proposed a novel deep memory network with an auxiliary memory for handling the relation between aspects and terms, based on the semantic relatedness, through an attention mechanism. The results of auxiliary memory were forwarded to main memory for capturing the context of each word for sentiment classification.

Gu *et al.* [142] discussed that aspects and their neighboring words should be given more importance than other long-distant words. They proposed a position-aware-bidirectional-attention network for mutually modeling the relation between aspect terms and sentence. They initially generated aspect-positional embeddings for each word in the corresponding sentence. And then concatenated the word embeddings and position embeddings to get the final hidden contextual representations of the aspects and input words to compute the attention weights for classification prediction. Moreover, Majumder *et al.* [143] also proposed a memory network architecture to model the connection between inter-aspects and its neighboring aspects. They employed GRU for promoting contextual information of words, which was further utilized by an attention mechanism for achieving aspect-aware-sentence representation. The final accurate representations of the aspects and sentiment classification was achieved after continuously iterating through the memory network. However, Wang and Lu [144] captured and modelled the structural dependencies between targets and sentiments, and between sentimental words, through a segmentation-attention-based LSTM for selecting sentiment words those have most impact on classification.

However, another challenge is to handle sentences that contain multiple aspects, as it includes two sub-challenges, first; to connect an aspect to the clause that contains its sentiment information, and second; to conclude sentiment for aspects that do not hold enough contextual or semantic information. Because, sometimes, sentences with conjunctions, e.g., but, not, also, though, however, only etc., are suitable to predict the sentiments for aspects, e.g., "Food is great, but I doubt about the freshness of meat". In this example, the positive sentiment of "food" and presence of conjunction "but" ultimately determine the negative sentiment for "meat". Another example, "The grocery list was short; I remember it contained only 5 to 7 items". In this example, the aspect "items" does not provide any sentiment unless we consider it with aspect "grocery list". Hence, the negative sentiment of "grocery list" cause "items" to have similar sentiment. To handle these challenges, Hazarika *et al.* [145] focused on all the aspects and the particular words of the sentence for generating aspect-sentence representations through an attention-based LSTM. Further, they captured inter-aspect dependencies by sequentially modeling aspect-sentence representations through another LSTM for concluding sentiment for aspects that did not hold enough contextual information. However, Wang *et al.* [15] handled word-level and clause-level information in the sentence through a hierarchical-aspect-specific-attention network for improved sentiment classification. They initially implemented elementary-discourse units to segment a sentence into different non-overlapping clauses. Next, they employed a BiLSTM and a word-level attention for encoding clauses' information and for capturing the importance of each word present in the clause, respectively. Further, they utilized another BiLSTM and a clause-level attention for computing the attention weights of each clause and representing their relative significance. Moreover, Lin *et al.* [146] adopted deep memory network for modeling inter-aspect-semantic dependencies between different aspects through semantic attention and contextual learning to finalize sentiments of all aspects. The attention exploited the information about every explicit aspect present in memory through semantic parsing. And the context-moment-learning module provided the complete context (background) of the particular aspects by learning the semantic distribution of the whole sentence.

### 4.2.2 Contextual-Semantic Sentiment Information

The impressive enhancement in attention mechanisms have considerably improved the abilities of NNs, and SA of the text is more becoming the contextual analysis of the text. Because the contextual scenario behind the text data derive meaningful actions for making things interesting and up-to-date. Therefore, a crucial step is the detection of the sentiment context about the given aspect (target) for correct sentiment prediction. Many researches have employed attention mechanisms for achieving semantic relatedness between targets and context words to capture the target information and to compute context representation for sentiment classification [128], [154]. Moreover, deep memory networks [129], LSTM [144], GRU [143], and positional information of aspects [142] has also been adopted to promote contextual-semantic sentiment information of words, along with attention mechanisms. For instance, Fan *et al.* [156] employed a BiLSTM via multi-grained-attention network to capture relationships between similar context words possessing similar/different sentiment polarities. The network considered the temporal interaction between words by consistently linking and fusing information between aspect terms and context words, with no information loss. The network assigned attention scores to context words with respect to their aspect terms and targets, and vice versa.

Attention mechanism also studied the attention difference of aspects sharing same context words. Moreover, Yang *et al.* [151] employed a multi-view co-attention network for modeling general semantics of sentiments, targets and context words. First, they learned improved feature representations of single inputs, POS and word-position features through low-dimensional embeddings. Next, they exploited three independent LSTMs and an attention to obtain the hidden states of sentiment words, targets and context words, and to capture the significant sentiment information from different representation subspaces at different positions. Further, Ma *et al.* [155] utilized LSTM and position-attention mechanism for computing the explicit position-contextual information between an aspect and its context words for processing multi-aspects and their sentiments within the sentence simultaneously.

But sometimes, simply relying on an attention model cannot solve the issue of contextual-semantic-sentiment information because performance degrades when the sentiment of a context word is sensitive to the given target (word). Therefore, Ma *et al.* [157] got inspired by the cognitive characteristic of humans and focused on more effective representation of each context word. They observed that only using word embedding as external memory is not sufficient, hence, they extracted location, POS and sentiment features through memory network to enrich the word representation of each context word. Each layer of model was designed to compute attention scores between aspects' representation and context words. Finally, aspect representations of last layer were used through a ReLU function for final sentiment classification. Overall, model showed better performance in distributing attention scores between words and in ignoring words without sentiment. Yang *et al.* [140] modelled long-sequences between words, after considering different word locations in a relatively even manner, for performing target-dependent-sentiment classification through a BiLSTM with additional attention layer(s) on top. One attention layer considered the context and intent importance of current input and target for computing attention score of each word through a dot-product mechanism. The other attention layer computed attention scores through a bilinear term. Further, Wang *et al.* [153] proposed six alternative target-sensitive-recurrent-attention-memory networks for capturing interaction between the aspects (targets) and their contextual sentiments. The target-sensitive memory networks were capable of handling both general and target-sensitive sentiments.

However, Qiu *et al.* [158] utilized a sequence-labeling CRF for predicting rating of reviews by considering aspects with their related context. The core component of the model was a probabilistic discriminative model, a variant of CRF, called SentiCRF, that built the list of term pairs where each element of the pair was acted as the context for their counterpart. This contextual information helped to assign appropriate sentiment scores to the term pairs.

## 5 Sentiment Evolution (SE)

SE, the third phase of AbSA, deals with the sentiment's dynamicity with time. SE captures researchers' attention for last two decades, as it depicts the social diversity that formulates the overall agreement in sentiment change [159]. The two major issues of SE are: the recognition of factors that opt people to change their sentiment, e.g., cognitive attitude, adopting the majority sentiment, social behavior and influence of heterogeneous confidence, and the prediction of SE over social media.

### 5.1 Recognition of Factors in SE

#### 5.1.1 Cognitive (Informational) Attitude

Cognitive attitude refers to the thoughts, perceptions and understanding of a certain aspect. It is basically an opinion that depicts the general knowledge of a person towards a certain aspect (object, event, entity, target or person), which compel him/her to change his sentiment towards certain event [160]. For example, the sentiment outcome on the mega events such as World Cup involved much dynamicity with the passage of time [161]. Keeping this factor in mind, Chi *et al.* [17] provided a theoretical framework that associated the affective-evaluation attitude with the cognitive-evaluation attitude to evaluate SE. They studied the attitude and predicted the decision-making psychology of people towards an event over a period. They assessed that the differences in the peoples' attitudes concerning pre-event and post-event are due to the information insights and understanding towards the particular aspects, that make them revise their sentiments with passing time. They clearly demonstrated that the context of a certain aspect (event) is the basic reason for decision making tendency of humans.

#### 5.1.2 Adopting the Majority Sentiment (Minority Avoidance)

Another issue involved in SE is the preference of majority sentiments. People instead of showing their own sentiment towards the aspect, adopt the neighbor's and relative's sentiment and avoid the linkage to the minor community holding different sentiment attitude. Fu and Wang [162] found that SE is basically based on majority-adaptation and minority-avoidance rule. The underlying network of their study was a majority-rule model in which people preferred to follow crowd to update their sentiment and broke the link with the community holding a dissimilar (minor) sentiment. They revealed that an increasing tendency of linking neighbors reduced the number of sentiments. Their investigation clearly demonstrated that like-minded people holding the same sentiment belonged to the single-community in the network.

#### 5.1.3 Social Behavior

Social behavior arises when the individuals interact with the community and its surrounding environment. During social interactions, the change of sentiment is determined by the social impacts like harmonization and divergence. Because sometimes individuals get influenced from their neighbors and make a decision, but, the probability still holds that an individual instead of following its community, devises its own sentiment [163], [164]. Chen *et al.* [165] also stated that social policies, relationships and norms have great impact on social evolution. They proposed three different social-acquaintance networks named kinship-priority-acquaintance network (KPAN), independence-priority-acquaintance network (IPAN), and hybrid-acquaintance network (HAN) based on the variations between the social cultures and policies. They found that KPAN always achieved fragmentations in sentiment due to the fact that individuals mostly believe in their relatives and neighbors for adopting sentiments. In IPAN, SE was based on the western values that encouraged independent decision about sentiments, but with consent discussion. HAN took into account both networks, i.e., KPAN and IPAN, and depicted that sentiment reach a consensus on a very large scale. The findings of these networks facilitated in computing and predicting SE under diverse associated networks, and also helped in forming rational cultural policies for public guidance.

#### 5.1.4 Heterogeneity of Confined Confidence and Influence (HCCI)

Sometimes, the fact of heterogeneity-confidence distribution over the network is ignored, in which people cannot communicate with each other due to different geographical locations or statuses in the society, but yet hold the same sentiment level. To address the issue, Liang *et al.* [166] examined the HCCI in discrete-time scenarios, where all agents updated their sentiment level in a synchronous manner after averaging their neighbor's sentiments. In the network, every cluster kept the value of sentiment for a finite time before promoting consensus of sentiments, but this was not always true. Moreover, to find the weighted and signed relationships between individual nodes in a heterogeneous network environment, Pengyi *et al.* [165] explored dynamic sentiment patterns within heterogeneous relationships. After conducting a series of simulations, they found that at a stable state the sentiment level depends on the degree of social communication between networks. They observed that when harmoniousness parameter increases within the networks, sentiments transit from the bipolarization to the consensus phase.

### 5.2 Predicting Sentiment Evolution Over Social Data

Predicting the changing social behavior of individuals on real-time applications is a complex task. Nguyen *et al.* [167] presented a statistical-machine-learning model for analysing the collective sentiment level. They further transformed their model for large structured networks; containing many individuals and tweets. They extracted aspects from history and then utilized them for predicting the sentiment change in future. Moreover, Guerra *et al.* [168] tracked the emotional reactions of social media users during continual changing events on twitter, such as. breaking news, political talk etc. They found that users are more driven by the positive thoughts instead of negative thoughts, and users preferred to present their extreme thoughts instead of average thoughts towards the events. By taking into account these extreme thoughts, they proposed a feature-representation approach that was capable of discovering new aspects by capturing frequent changes on sentiment level caused by the real-world events. Lumin *et al.* [169] presented a hierarchical multidimensional model that first captured the non-redundant sentiment patterns towards the event, and then discovered the closed sentiment patterns through a clustering algorithm. The algorithm also maintained a sentiment vector that hold reasons behind changed sentiments. The model focused on the user-level sentiment dynamicity and conducted a study on real dataset, i.e., "Japanese Earthquake" in March 2011. Charltron *et al.* [170] observed the dynamic communicability of evolving networks to recognize the top communicators on twitter. First, they computed the initial sentiment of the communities and then detected correlation between the loss of users through a community-detection algorithm. They monitored stable connected twitter communities over a time-scale of months, and found that the people who have highest communicability-broadcast directories generally show positive sentiment as compared to ordinary users. They also found that every community maintain a stable sentiment level and remain connected by sending messages, but when a community shows a temporary large deviation from its usual sentiment, then some communities hold all its users and some communities lost a relatively small number of users.

## 6 Discussion and Future Research Directions

To achieve excellent performance from NLP and specifically AbSA requires a lot of effort. Aspect extraction and sentiment score determination are the core challenges of AbSA, which could not be handled through single-general solution. Instead, researchers should consider many sub-issues and sub-challenges for resolving the major challenges. These sub-challenges would develop an effective tool for AbSA and increase the sentiment classification performance (to some extent) at aspect-level. Some of them are discussed in this section.

### 6.1 Data Pruning and Cleansing

Mostly during the preprocessing phase, punctuation marks, common words, special characters, slangs and pronouns are removed from the text. To our perception, all of them make little contribution in analysing sentiment polarity from opinionated text. But the stop words and the redundant terms should be eliminated through an effective pattern-based approach.

In preprocessing, a multiple domain-specific lexicon would also be an interesting development that will produce distance metrics, integrate fuzzy membership of unclassified reviews and perform automatic domain-labeling. It could also be utilized with AE techniques to enrich text with significant information (lexical).

### 6.2 Cross-Domain-Transfer Learning

Supervised approaches are convenient for dealing with labeled data, but relying on large training datasets make the task less efficient. Generally, the efficiency of AE process compromises during handling unlabeled datasets, and might fail when applying it on a new domain, e.g., a model trained on restaurant data is not applicable on hotel data. No doubt, it is hard to grasp that there would be a general model that will perform reasonably good on all domains. However, model representations could be enhanced by pre-training and fine-tuning process, if accompanied by an efficient self-attention mechanism to carry out cross-domain-transfer learning. Because, self-attention network has the capability to deal with complex data by relating input words according to their context and positional information. This challenge, we believe, will be a new era in the field of AbSA, but it requires proper advancements for text representation, e.g., statistical and linguistic features, and label propagation with effective transductive learning.

### 6.3 Contextual-Semantic Relationships

Semantic information is compulsory to associate words with sentences according to their contextual information, which could be helpful in the extraction of explicit and implicit aspects, neutral sentiment expressions and complex text, e.g., negation words (shifting words), from the data. Based on semantic information, relationships between different data objects could also be mapped to improve sentiment classification accuracy. Moreover, the inclusion of contextual-semantic information, e.g., n-grams, dependency and syntactic relations, and likeness between sentences, would also be advantageous for upgradation of knowledge extraction process and for handling complex scenarios, e.g., "We went to a Pakistani restaurant and they offered us 5 to 6 choices of cocktails", here, "choices of cocktails" should be considered as a positive sentiment but normally taken as neutral. Another example is "Try the hand ripped bread", in this, the word "try" itself is not sentimentally charged, but it carries sentimental meaning when considered in the right context.

### 6.4 Aspect Summarization

Aspect summarization is entity-centric; it aims to produce brief summaries which are relevant to particular aspects (entities) and their sentiments. These summaries could be created by context-dependent words, negation words, similar sentiment words etc., but the challenge is to introduce a solution that will perform improved personalized summarization and give clear explanation on recommended aspects from the application. However, the actual presentation totally depends on the requirements and needs of the particular application.

### 6.5 Predicting Dynamicity of Sentiment

Some factors for sentiment transition might be little 'trust in government' and some 'political issues'. Therefore, social context should be improved to track sentiment at user, group and multi-group level. This will help to understand the behavior and complex-posting patterns of social media users. The dominant patterns will analyse the SE in more detail, and will also achieve different relationships between separated groups to produce more informative social contexts. Most of the time, prediction model computes the evolving sentiments of the existing users, but to validate the effects of new users on real data is a challenging research task in itself.

### 6.6 Multimodal SA

Lastly, as social media is not just overwhelmed by the text data, it also contains images, videos, emoticons, stickers etc., which depict user behaviors and attitudes towards the scenario. Therefore, it would be interesting to perform unification on such multimodal data by devising new approaches for extracting semantics of visual features. This fusion of cross-modal features will help to achieve more comprehensive aspect analysis from the user-generated content over social media. Moreover, cognitive techniques could also be adopted for reading and studying comprehensive skills and behaviors of human beings through machine intelligence imitation. To have more understanding on the topic, we refer our readers to [171].

However, researchers should also ponder upon other issues, like, preference of authors, emotional (emotional characteristics) analysis and computation etc. Apart from essential elements, AbSA deals with many other challenges which are not only limited to aspects' quality and flexibility. For instance, Robustness; to cope with informal writing style on user-generated content, e.g., spelling mistakes, grammatical errors, non-dictionary words, slang words, special characters, emoticons etc., for expressing sentiment. Scalability; efficiency of the system as the problem grows and also as the system grows. Learning rate decay; the learning time of system should be reduced over time. Other major problems are overfitting reduction and improved regularization over predicting large NNs. One more is max-pooling; to make assumptions about different aspect features. Finally, an approach should always learn to stop when performance starts to degrade.

The field of AbSA is at the never-ending stage where researchers are contributing day-by-day to satisfy it at several levels.

## 7 Conclusion

The survey has explored a very important research domain in the field of NLP, i.e., Aspect-based Sentiment Analysis (AbSA); a subfield of sentiment analysis that has accomplished many excellent researches. The survey has stated the thorough overview of the recent progress in AbSA by depicting the state-of-the-art deep-learning techniques fashioned in locating the target, which can be an entity, or it can be an aspect related to a target or an entity, their relationships, their respective sentiments and sentiment evolution dynamicity. An issue-based categorization of the recent solutions is presented each contributing towards improving the process of aspect extraction, aspect sentiment analysis or sentiment evolution. Key challenges are included as future research directions, which should be considered to achieve excellence in sentiment classification at aspect-level. Our survey can act as a foundation for researchers who want to know the recent progress of the field and help them formulate general strategies which would be applicable to most of the scenarios.

## Acknowledgments

The authors would like to thank editors and reviewers for their valuable comments and suggestions, which certainly improve the quality of this survey. The research work was supported by "National key research and development program in China" (2019YFB2102300); "the World-Class Universities (Disciplines) and the Characteristic Development Guidance Funds for the Central Universities of China" (PY3A022); Ministry of Education Fund Projects (18JZD022 and 2017B00030); Shenzhen Science and Technology Project (JCYJ20180306170836595); Basic Scientific Research Operating Expenses of Central Universities (No. ZDYF2017006); Xi'an Navinfo Corp. & Engineering Center of Xi'an Intelligence Spatial-temporal Data Analysis Project (C2020103); Beilin District of Xi'an Science & Technology Project

(GX1803). We woould like to thanks them for providing support.

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