World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:16, No:2, 2022

# Fine-Grained Sentiment Analysis: Recent Progress

Jie Liu, Xudong Luo, Pingping Lin, Yifan Fan



*Abstract*—Facebook, Twitter, Weibo, and other social media and significant e-commerce sites generate a massive amount of online texts, which can be used to analyse people's opinions or sentiments for better decision-making. So, sentiment analysis, especially the fine-grained sentiment analysis, is a very active research topic. In this paper, we survey various methods for fine-grained sentiment analysis, including traditional sentiment lexicon-based methods, machine learning-based methods, and deep learning-based methods in aspect/target/attribute-based sentiment analysis tasks. Besides, we discuss their advantages and problems worthy of careful studies in the future.

*Keywords*—Sentiment Analysis, fine-grained, machine learning, deep learning.

## I. Introduction

LOTS of the data reflect opinions and sentiments that people express on public forums such as Facebook, Twitter, microblogs, blogs, and e-commerce websites. The rapid development and popularity of the Internet inevitably lead to a significant increase in the amount of online data [1], and there are more and more data on opinions and emotions. The academic community and industry pay lots of attention to Sentiment Analysis (SA), hoping to help people concerned to make a better decision if they can understand these opinions and sentiments.

In particular, recently fine-grained SA [2], [3], [4] has received extensive attention from researchers. Fine-grained SA is the SA of phrases and words. The premise of the words of text sentiment orientation analysis mainly refers to the evaluation of the word extraction, and its sentimental tendencies (*commendatory*, *derogatory*, or *neutral*), strength (*hate*, *disgust*) sort. Fine-grained SA can be carried at two levels: 1) *attribute-level*, at which it judges whether or not the sentimental polarity is contained in a comment text for a particular attribute; and 2) *aspect level*, at which it identifies the sentiment polarity of a specified aspect in a sentence [5]. In the beginning, most researchers called tasks like Table I attribute-level SA, and later more and more researchers called it aspect-level SA. There is no apparent distinction between attribute level SA and aspect level SA.

Coarse-grained SA is another kind of SA, which is for the overall propensity prediction of massive data sets [6], [7]. Table II summarises the tasks of SA of coarse-grained and fine-grained. Coarse-grained SA is not enough for practical applications. For example, "I like the salad at KFC", coarse-grained SA only knows that the evaluator expresses positive sentiments, but we need to know that the evaluator expresses sentiment "like" to "salad" in "KFC". In application, the research focus of SA tasks has changed from coarse-grained SA to fine-grained SA. Thus, in this paper, we focus on surveying fine-grained SA.

Although some researchers also survey SA, our survey in this paper is different from theirs. In 2019, Prabha and Srikanth [8] analysed some methods of SA on the sentence level and aspect level; Tedmori and Awajan [9] outlined the main tasks and applications of SA, and also summarised and categorised the state-of-art methods for SA; Gao and Wang [10] compared the application of several SA platforms with open source review datasets. In 2020, Lin and Luo [11] surveyed machine learning-based SA methods; Lin and Luo also [12] reviewed various applications of sentiment analysis; Lin, Luo, and Fan [13] surveyed deep learning-based SA methods. In 2021, Guo, Yu, and Wang [14] summarises the state-of-art of body level text SA, but it does not include new methods from 2021. Our survey in this paper is from the above ones at two aspects: (1) they did not cover the work published in 2021, but we do; (2) they did not focus on fine-grained SA, but we focus on surveying the fine-grained SA, including sentiment lexicon-based methods, machine learning-based methods, and deep learning-based methods. In particular, we discuss the challenges faced by fine-grained SA and future development directions.

The survey of fine-grained SA is necessary and valuable for the following three reasons. First, there is currently little survey for fine-grained SA tasks. The existing ones are based on method classification, and we survey them according to their tasks. Second, fine-grained SA tasks are essential. Whether in online business or offline business applications, fine-grained SA can make good contributions. Third, since fine-grained SA is on attribute-level or aspect-level, which can expose more detailed information, it is more complicated and challenging than traditional sentence-level and chapter-level SA tasks.

The rest of this paper is organised as follows. Section II briefs sentiment lexicon-based methods for fine-grained SA. Then, Sections III and IV discuss deep learning-based methods and other learning-based methods for fine-grained SA, respectively. Finally, section V concludes the paper with future work.

## II. Sentiment Lexicon Based Methods

This section discusses the sentiment lexicon construction and SA based on the sentiment lexicon.

This work was supported by the National Natural Science Foundation of China (No. 61762016) and Guangxi Key Lab of Multi-source Information Mining & Security (No. 19-A-01-01).

The corresponding author: Xudong Luo (luoxd@mailbox.gxnu.edu.cn)

Jie Liu, Xudong Luo, and Pingping Lin are with Guangxi Key Lab of Multi-Source Information Mining & Security, College of Computer Science and Engineering, Guangxi Normal University, Guilin 541004, China.

Yifan Fan are with Guangxi Key Lab of Multi-Source Information Mining & Security, School of Computer Science and Technology, Soochow University, Suzhou 215031, China.

TABLE I
EXAMPLES OF FINE-GRAINED SA

| Example | Entity | Attribute or aspect | Opinion | Sentiment category |
|---|---|---|---|---|
| I like KFC's salad, but there is too noisy. | KFC | food, environment | like, noisy | food-like, environment-unlike |
| The phone has high pixels, good image quality and clear photos. | mobile phone | pixels | high, good, clear | pixels-positive |
| Waiters are very friendly and the pasta is simply average. | waiter, pasta | service, food | friendly, average | service-positive, food-negative |

TABLE II
COMPARISON OF FINE-GRAINED SA AND COARSE-GRAINED SA

| Type | Level | Task |
|---|---|---|
| Fine-grained SA | attribute | Identify and evaluate object attributes; attribute-oriented sentiment classification. |
| | aspect | Aspect recognition; aspect-oriented SA. |
| Coarse-grained SA | sentence | Sentimental information extraction; sentence polarity recognition. |
| | chapter | Sentence extraction; sentimental information extraction; text polarity recognition. |
| | massive information | Recognition of polarities in various chapters; integration of sentimental information in massive chapters. |



### A. *Construction of sentiment lexicon*

The primary process of the sentiment lexicon-based methods consists of data collation, lexicon construction, sentiment word matching, calculation of sentiment score, and method evaluation. This method determines a sentiment tendency of a word in a document by matching a word in a sentiment lexicon. So the construction of the lexicon is essential for SA.

There are five ways for constructing such a lexicon. The first is a lexicon-based method. Based on the seed sentiment lexicon, it expands into the required sentiment lexicon. For example, Prakash and Aloysius [15] discuss lexicon-based approaches to SA. They address three critical issues of sentiment analysis. 1) the same word with different meanings in different contexts; 2) the complexity of acronyms, emoticons, and contextual words; and 3) the optimisation of lexicon-based approach performance, especially the accuracy of SA. Chinese popular seed sentiment lexicons include HowNet Chinese and English sentiment lexicon, Taiwan University's Chinese sentiment polarity lexicon "NTUSD"[16], and Dalian University of Technology Chinese sentiment vocabulary ontology library. In addition, there are two ways to expand a seed sentiment lexicon: 1) manually collect seed words, and 2) use a large-scale Chinese corpus to train new words to obtain an extended thesaurus for SA.

The second method of constructing a sentiment lexicon is domain-specific. Jiang, Guo, and Liu [17] build a sentiment lexicon suitable for social media text SA. Gao *et al.* [18] work out a sentiment dictionary for SA in News Domain.

The third is a corpus-based method. For example, according to the sentiment polarity of some vocabulary in a domain corpus, Rouces, Borin, and Tahmasebi [19] use the linguistic database to calculate the sentiment polarity of another vocabulary to work out a sentiment lexicon.

The fourth is a machine learning-based methods [20], [21]. Using a machine learning method to construct a sentiment lexicon treats the construction task as a word-level sentiment classification task. The general process is first to build the feature vector of a word, then use the existing sentiment lexicon to determine the sentiment polarity of some words, and finally build a word-level sentiment classifier for predicting the sentiment polarity of other words.

The fifth is deep neural network-based methods [22], [23], which have two types. One is to learn word vectors containing sentiment information through the deep neural network [24], [25], then use some words with *known* sentiment polarities to train a sentiment classifier. Finally, the sentiment classifier predicts words with *unknown* sentimental polarities. The other is to integrate the sentiment words into the learning process of the deep neural network [26].

These five ways of constructing a sentiment lexicon can get a considerable number of words. However, the meaning of the words may change in different contexts, which leads to a polysemy phenomenon. So the constructed sentiment lexicon does not represent these ambiguous words very well. Moreover, a text for SA likely contains dialects, colloquial words, and network terms, making it even more difficult to be understood. Even if people can understand, different people may have different opinions for the same sentence. As a result, this could cause deviations when segmenting words.

Although building a high-quality sentiment lexicon is the basis for SA, it is not easy to map an emotion expressed in a text to an accurate sentiment. For example, "despairful" includes "fear" and "sad", then "despair" cannot be mapped to "fear" or "sad". This brings a significant challenge in sentiment annotation for SA. To address the issue, Li *et al.* [27] propose an automatic construction method of sentiment lexicon based on compound sentiment psychology theory. It maps sentiment words into a sentiment space and uses a cascade clustering algorithm to annotates different sentiment categories. They eventually built a new composite sentiment lexicon called EmoMix for complex SA. Their experiments show that their method is better than the state-of-the-art ones in both the word and sentence-level primary classification performance.

Wang *et al.* [28] propose a learning framework for constructing domain-specific sentiment lexicons from online customer reviews, called User Generated Sentiment Dictionaries (UGSD). It first selects a set of sentiment word candidates; then coverts the entities involved in the comments into corresponding rating symbols; next, does co-occurrence proximity learning; finally, calculates candidate sentiment phrases of z-score to determine the lexicon by calculating cosine similarity. UGSD is suitable for various user-generated content from different domains to build domain-specific sentiment lexicons. Besides, UGSD does not need to be based on a seed lexicon. It is wholly data-driven and automatically learns sentiment words in building a lexicon, which is more conducive to obtaining high-quality fine-grained sentiment lexicons in different fields.

### B. Sentiment lexicon-based methods

The core of sentiment lexicon-based methods is "lexicon + rules". A sentiment lexicon is used mainly for judging the polarity of sentiments according to specific rules. Therefore, a lexicon-based method for SA essentially relies on the quality of sentiment lexicons and judgment rules. Since humans construct both lexicon and rules, the pros and cons of such a method largely depend on the humans and their prior knowledge, so its promotion ability may be insufficient.

The classic method of this kind was done by Turney and Peter [29] in 2002. It is a method for calculating online sentiment, called PMI-IR. Specifically, they calculate the mutual information distance between all sentimental words in a sentiment lexicon that accumulates all opinion words in comment sentences about products and get the sentimental polarity of the commentary about the attributes of a product.

To do SA of tweet data from consumers of ASUS, ACER, and Apple laptop products, Purba [30] proposes a lexicon-based method for fine-grained SA in the form of positive, neutral and negative sentiment. They used InSet (Indonesian Sentiment Dictionary) built by Fajri Koto and Gemala Y. Rahmaningtyas. As a result, the SA shows that the three laptop brands have more positive emotions than negative ones. In particular, in terms of Net Brand Reputation, ASUS products have the best reputation sentiment with a score of 25%, followed by ACER with 24%, and Apple with 7%. Regarding Brand Favorable Talkability, ACER has the best reputation with a BFT Rating of 65%, followed by ASUS with 62%, and Apple with 45%.

Han, Han, and He [31] propose a lexicon-based method for fine-grained SA. First, they use sentiment lexicon SentiWordNet to identify the sentiment words in the reviews of the dataset and mask them, then use the masked sentiment pre-trained model to predict the masked words, and finally, they use the multi-label classification model to detect aspect topics and aspect-level sentiment. Their experiments show that their model achieves an accuracy of 96.6 and 87.6 for aspect detection and aspect-level sentiment classification sub-tasks, respectively, on SemEval2014 dataset, more than 2.9% and 1.9% higher than previous works for the aspect detection and sentiment classification, respectively. It also outperforms the baseline BERT model by 28.1% and 7.4%. However, does it outperform GTP-3? It is worth studying in the future. Generally speaking, it is worth using various pre-trained models for fine-grained SA in the future.

Soumya and Pramod [4] do a fine-grained SA on Malayalam tweets by using sentiment lexicon and machine-learning. They classify the tweets into positive, strongly positive, negative, strongly negative, and neutral sentiments. The lexicon-based method achieves an accuracy of 84.8%. However, the machine learning methods of Support Vector Machine (SVM) and Random Forest (RF) are better than the lexicon-based method. Specifically, the SVM (kernel = linear), SVM (kernel = RBF) and RF with the Sentiwordnet feature vector got an accuracy of 92.6%, 92.9%, and 93.4%, respectively.

### C. Remark

The sentiment lexicon-based methods are simple but effective in classifying the sentiment of a text. However, since such a method is derived from the process based on grammatical rules, professionals with grammatical sensitivity must construct the sentiment lexicon.

There are two significant shortcomings of the methods.

1) Many sentiment lexicons can only be used to classify sentiment words into positive and negative ones, lacking the division of the degree of expression of the polarity of sentiment words. Furthermore, due to the simple cumulative calculation of sentiment scores, there is a significant error in the final classification results. 2) This kind of method mainly depends on the design of the sentiment lexicon's coverage of the sentiment polarity scores. Thus, the construction of a lexicon is the focus and difficulty of such a method. Therefore, in the future, it is worth finding more effective ways to expand or construct a sentiment lexicon based on the existing seed lexicon and building a high-quality, comprehensive, but not domain-specific sentiment lexicon.

## III. Deep Learning Based Methods

This section discusses some Deep Learning (DL) based methods for fine-grained SA.

### A. Aspect-based SA

Aspect-based SA (ABSA) classifiers texts by aspect and identifies the sentiment attributed to each one. People use ABSA to analyse customer feedback by associating specific sentiments with different product or service aspects. So, it is a text classification problem, and thus researchers use various deep learning methods to solve it.

*1) Neural network-based method:* Liu and Shen [32] propose a novel neural network structure, named the Gated Alternate Neural Network (GANN), to learn informative aspect-dependent sentiment clue representations. In GANN, a specially designed module, Gate Truncation RNN (GTR), is used to learn the emotional clues that depend on aspects of learning information.Their method try to remove some limitations of previous SA methods, such as not being good at capturing long-distance dependency. Their experiments on four Chinese and three English datasets show that GANN achieves state-of-the-art results and is lingual-independent.

*2) LSTM based method:* Peng *et al.* [33] propose a new subtask under ABSA, called Aspect Affective Triple Extraction (ASTE). In particular, the solver for this task needs to extract triples (what, how, why) from the input. These triples show the target aspect, their emotional polarity, and why they have this polarity (*i.e.*, reason for opinion). At the first stage, they have obtained many aspects with sentiment polarities and many opinion expressions. In the second stage, the goal is to pair up aspects with the corresponding opinion expressions. Their experiments validate the feasibility and effectiveness of their model and set a benchmark performance for this task.

*3) IATN-based Method:* Zhang *et al.* [34] propose Interactive Attention Transfer Network (IATN) for cross-domain sentiment classification. The unique feature of IATN lies in the use of an interactive attention mechanism to elicit important information of sentiment classification from sentences and aspects. IATN contains two attention networks, which identify common features between domains and extract various aspects of information. IATN models sentences and aspects separately and interactively learn the sentences and aspects. In their work, cross-domain refers to the reviews of different products in Amazon. There are few studies on aspects of cross-sector sentiment classification. So, in the future, it is worth developing a general SA model for cross-domain (*e.g.*, Amazon product reviews).

*4) LSM-based Method:* To simultaneously encode both the syntactic dependency edges and labels information in a unified manner, Zhao *et al.* [35] first propose a novel Label-wise Syntax Memory (LSM) network. In addition, they use the Bert pre-training language model to provide a rich context for the target aspect. The results show that their models outperform the best baseline and achieve new state-of-the-art performances. They also further analyzed and proved that it is necessary to encode sufficient syntax dependency knowledge for tasks and showed that their LSM encoder effectively modifies these syntax attributes.

*5) T-GCN:* In ABSA studies, for using word relations to analyse context and aspect words, people widely use neural graph-based models. However, most of these studies only use word relations without considering their types, so they cannot distinguish the important relations and learn from different layers of graph-based models. To address the issues, Tian, Chen, and Song [36] propose a method to explicitly consider word relation types for ABSA by using Type-aware Graph Convolutional Networks (T-GCN). In T-GCN, the attention mechanism distinguishes different edges (relationships), and the attentive layer ensemble learns from different layers of T-GCN comprehensively. Their experiments show the validity and effectiveness of their method on six English benchmark datasets. They also do experiments to analyse the contributions of each component in their method and demonstrate how different layers in T-GCN help quantitative and qualitative ABSA.

*6) HSCN:* Lei *et al.* [37] propose a kind of Human Semantic Cognition Network (HSCN). They first used a word-level interactive perception module to capture the correlation between context words and a given target word. Then, they used a target-aware semantic distillation module to generate target-specific contextual representations for aspect-level emotion prediction. Finally, they designed a semantic deviation measurement module to measure the semantic deviation between a specific target context representation and a given target. The experiments demonstrate that HSCN achieves impressive results. In the future, it is worth trying to apply their network to longer texts and model the cognitive process of human reading better.

*7) MGAN:* Li *et al.* [38] find that the existing public corpus for SA in specific aspects is rare, which hinders the application of neural networks in SA. To address the issue, they regard the resources in the coarse-grained general aspect tasks as the source domain and the fine-grained specific aspect tasks as the target domain and transfer the knowledge learned from the source domain to the target domain. The two tasks with different granularities have complex challenges, such as task differences and feature distribution differences. Thus, they propose the Multi-Granularity Alignment Network (MGAN) to align granular representations across domains to solve the inconsistencies between coarse-grained and fine-grained domain features. Besides, they use Coarse2Fine to help coarse-grained general aspect tasks modelled at a fine-grained level. MGAN's accuracy and Macro-F1 value on a laptop review dataset, restaurant review dataset, and Twitter are superior to those previous algorithms. It is worth studying whether the specific aspect terms should be given in advance or identified during the classification process for the classification migration.

*8) HGMN:* The current LSTM-based mainstream models for the ABSA method uses LSTM to model contexts [43]. After obtaining the contextual vector representation, they use the attention mechanism to generate the attention weight vector. However, some people argue that introducing the attention mechanism in ABSA may lead to irrelevant words and noise when predicting the sentimental polarity of certain aspects, especially when dealing with long and complex sentences. The context output after the attention mechanism is directly input to the softmax layer. This layer cannot handle the recognition of particular sentences (*e.g.*, negative sentences, irony sentences) or even the noise caused by the attention mechanism. The existence of these factors destroys the performance of such a model.

To address the issue, Ran *et al.* [39] propose a Hierarchical Gate Memory Network (HGMN) for ABSA tasks. First, they use HGMN to learn how to select the related part about the given aspect while keeping the sentence's original sequence structure. Then, they apply CNN on the final aspect-specific memory to extract the feature representation of a sentence. Their experiments on SemEval 2014 show that HGMN outperforms state-of-the-art attention-based benchmarks. The authors think that it is worth studying the dependency analysis tree and designing better regularisation terminology to guide the hierarchical gate mechanism in the future.

*9) DTLM:* To make better use of the unlabelled data in the target domain, Cao *et al.* [42] present a deep transfer learning mechanism (DTLM) for fine-grained cross-domain sentiment classification. They introduced BERT as a feature encoder and used KL divergence to design a domain model to eliminate the feature distribution between the source and target domains. The experiment proved the effectiveness of their proposed method.

*10) EIE-CBiL-Att:* To improve aspect detection and sentiment polarity identification, Sindhu and Vadivu [40] propose an enriched input embedding with the token, orientation, grammatical function, field and intensity components in the embedding stage. And they use the convolution kernel to refine the pattern extraction, and in the end, use the attention mechanism to improve performance. The experimental results show that their program method brings the best-enhanced

TABLE III
SENTIMENT ANALYSIS ALGORITHM BASED ON DEEP LEARNING.

| Reference | Task | Learning model | Data set |
|---|---|---|---|
| [32] | Aspect target SA | GANN | Multi-language and multi-source datasets:Camera, Car, Notebook, Phone, Restaurant Laptop Twitter |
| [33] | Aspect sentiment triplet extraction | Bi-LSTM | SemEval 14 Laptop, SemEval 14–16 Restauran |
| [34] | Aspect extraction, domain classify, sentiment classify | IATN-LSTM | Amazon reviews dataset: Book, DVD, Electronics, and Kitchen |
| [36] | Aspect category SA | T-GCN | SemEval-14: Laptop, Restaurant, Twitter; SemEval 15-16: Restaurant; MAMS |
| [37] | Aspect category SA | HSCN | SemEval-14: Laptop, Restaurant; Tweets |
| [38] | Fine-grained AT | MGAN | YelpAspect, SemEval-14: Laptop, Restaurant, Twitter |
| [39] | Aspect SA or target SA and aspect category SA | HGMN | SemEval-14: Laptop, Restaurant, Twitter |
| [40] | Aspect SA and aspect category SA | EIE-CBiL-At | SemEval-14: Restaurants, Laptops; SemEval-16: Restaurants; Twitter |
| [41] | Aspect extraction and sentiment classification | CNN+GRU | Hotels and Cars |
| [42] | Fine-grained cross-domain sentiment classification | DTLM | YelpAspect, SemEval 2014:Laptop, Restaurant, Twitter |

Open Science Index, Computer and Information Engineering Vol:16, No:2, 2022 publications.waset.org/10012408.pdf

performance compared to the near closer designs.

*11) CNN+GRU:* The sentiment polarity of a sentence is determined by its content and has a relatively significant correlation with the corresponding aspect. For this reason, Zhao *et al.* [41] propose an ABSA model, a combination of Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU), which utilises the local features generated by CNN and the long-term dependence of GRU learning. Their experiments show that the proposed model has achieved excellent performance in aspect extraction and sentiment classification.

### B. Attribute-based SA

There are some methods for attribute-based SA. For example, Ghosh, Kotekal, and Chakraborty [44] study attribute-based SA in marketing and accurately survey consumer sentiment. To overcome the difficulty of obtaining data, they provide a method for effectively collecting consumer reviews. They also do SA based on topic classification. The difference is that the two research areas are different. In the future, it is worth studying more similar topics in the field of the market.

So far, only a few studies have relied on syntactic features to explicitly derive sentiment and the aspect-based sentiment classification task from capturing implicit contextual word relationships. To derive the sentiment direction of OCR by capturing implicit word relationships and combining domain-specific knowledge, Bansal and Srivastava [45] propose a new method: Hybrid Attribute-Based Sentiment Classification (HABSC). First, they detect the corpus's most common binary and ternary phrases and then perform part-of-speech tagging to retain aspect descriptions and opinion words. Then, they use TFIDF (term frequency-inverse document frequency) to represent each document. Finally, they assume that each review is a mixture of weighted attributes and sentiment labelling attributes, thus finding the sentiment orientation of each review. Their experiments show that the classification accuracy of HABSC significantly exceeds that of various state-of-the-art methods.

To extract implicit context-sensitive sentiment and handle slang, ambiguous, informal and special words used in CGC, Bansal and Srivastava [46] propose a novel text mining framework. Firstly, POS (part of speech) tagging is used for detecting aspect descriptions and sentiment-bearing words. Then, LDA (latent Dirichlet allocation) groups similar aspects and form an attribute. Finally, to find the context-sensitive sentiment of each attribute, cosine similarity is used with a set of positive and negative seed words. Their experimental results show that the proposed method effectively discovers product attributes and corresponding contextually perceived emotions.

### C. Remark

Table III and Fig. 1 compare some fine-grained SA tasks. Fig. 1, we also show the accuracy, Macro-f1, precision and Recall of each model. Besides, since some papers did not evaluate their systems according to all the criteria, there are no corresponding evaluation results in the figure. Although many algorithms use different data sets, their results are not very different, and the accuracy is almost below 90%. Therefore, It is believed there is still room for improvement. At the same time, it found that many articles only calculate two indicators. And To compare with other methods, it is better to calculate all four criteria.

There SemEval-2014 Task 4 [47], SemEval2015 Task 12 [48], SemEval-2016 Task 5 [49], SemEval-2017 Task 5 [50], SemEval-2018 Task 1 [51], and SemEval-2019 Task 3 [52] are fine-grained SA data sets widely used. At present, research in this direction of fine-grained SA has two obvious limitations. Firstly, existing data sets are small, and the annotations are incomplete, making more real SA applications impossible. Secondly, insufficient research on cross-lingual and cross-domain transfer capabilities has led to poor practical usability of research work. Some researchers (*e.g.*, [53]) also try to use transfer learning for the SA tasks in low-resource fields.

## IV. OTHER MACHINE LEARNING-BASED METHODS

This section discusses some fine-grained SA methods based on machine learning algorithms other than deep learning algorithms.

### A. BERT-based method

*1) End-to-end ABSA:* Li *et al.* [53] use BERT [60] modelling capabilities to do end-to-end ABSA. Unlike the current work, they standardise the comparative study by consistently utilising the hold-out development dataset for model selection. Their experimental results show that BERT-trained word

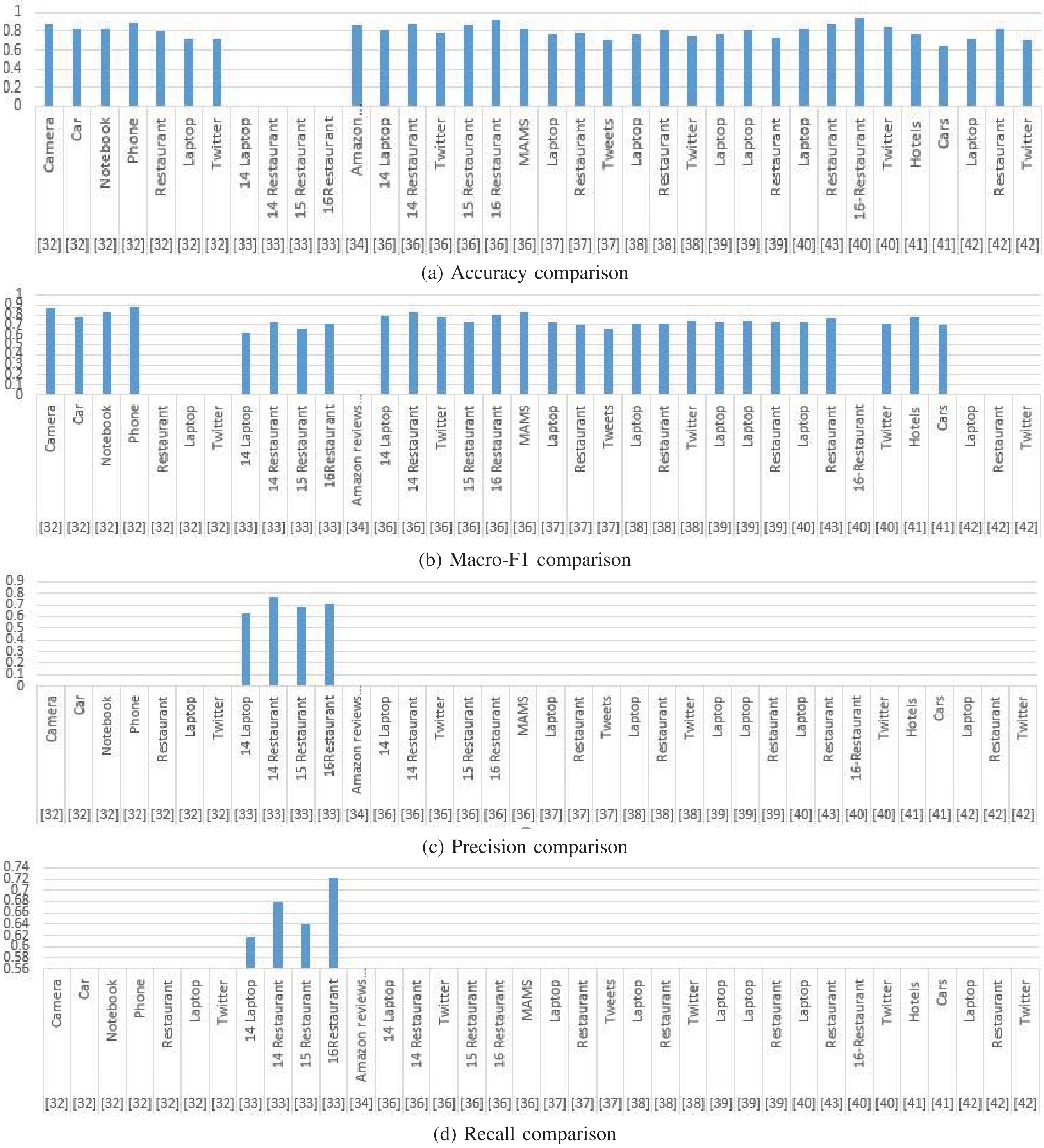


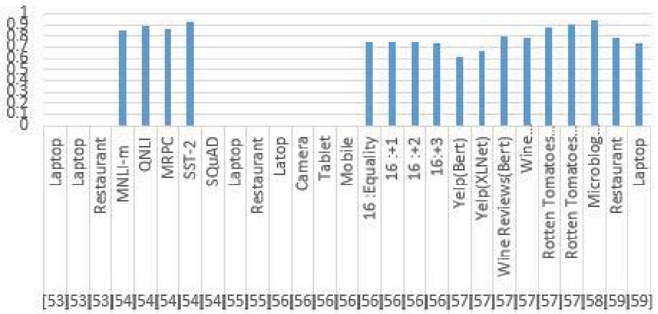

Fig. 1. Performance comparison of various deep learning-based methods for fine-grained SA

vectors improve the accuracy and the overfitting problem of model classification.

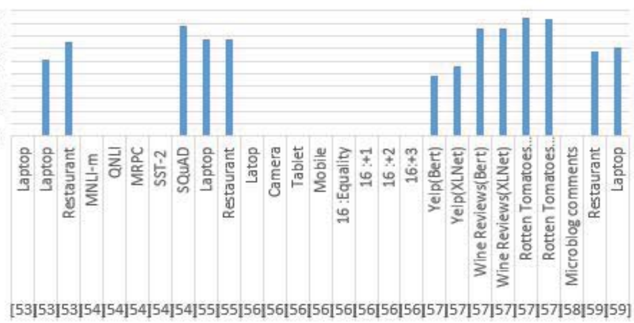
*2) CASC:* ABSA has two sub-tasks: aspect extraction and aspect-level sentiment classification. Most existing BSA methods use supervised learning algorithms with labelled data to do the two sub-tasks independently. Nevertheless, it is difficult and costly to obtain such labelled sentences. To address the issue, Kumar *et al.* [55] propose a BERT-based semi-supervised hybrid model for ABSA, called CASC. The model jointly detects an aspect and its associated sentiment in a given review sentence. Specifically, first, they use a small set of seed words for each aspect and sentiment class to construct respective semantically coherent class vocabularies. When using seed words to build a vocabulary, they input a

TABLE IV
SENTIMENT ANALYSIS ALGORITHM BASED ON MACHINE LEARNING.

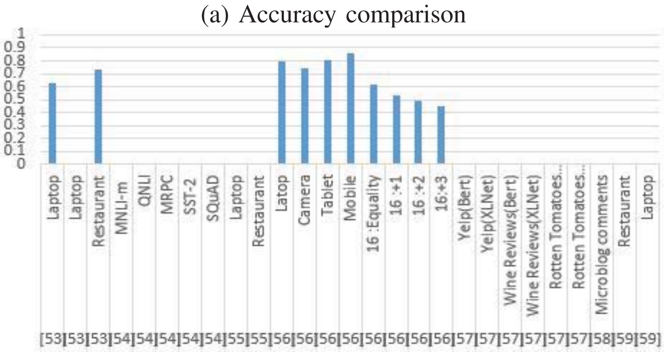
| Reference | Learning Model | Advantage | Disadvantage | Data set |
|---|---|---|---|---|
| [53] | End-to-end ABSA | Improve the accuracy | Long training time | SemEval 14-16: Laptop; SemEval 14–16 Restaurant |
| [54] | MEJD | Increased accuracy | Long training time | MNLI-m, QNLI, MRPC, SST-2, SQuAD |
| [55] | CASC | High accuracy | only be used in English | SemEval 16:Laptop and Restaurant |
| [56] | LISA | Easy to use in different languages | No use of language resources | Persian dataset:Latop, Camera, Tablet, Mobile; SemEval 2016 |
| [57] | TL | High classification accuracy | Long training time | Yelp, Wine Reviews, Rotten Tomatoes Movie |
| [58] | PLSA+K-means | High classification accuracy | Low generalization ability | Microblog comments |
| [59] | TM based ABSA | human-interpretable learning | Accuracy is not too high | SemEval 2014: Restaurant and Laptop |



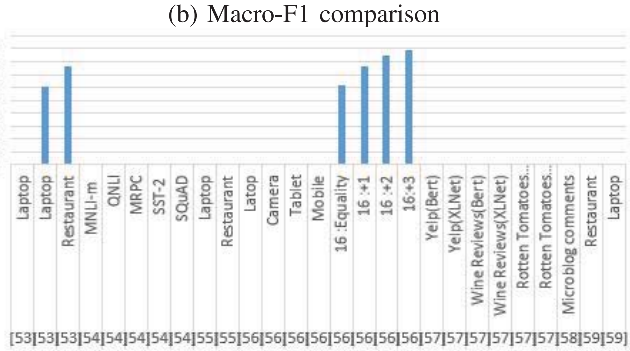

(a) Accuracy comparison




(b) Macro-F1 comparison




(c) Precision comparison




(d) Recall comparison

Fig. 2. Performance comparison of various machine learning-based methods for fine-grained SA

sentence to BERT to predict the word to find all the labelled replacement candidates in the sentence. Then, they use these constructed vocabularies and POS tags to label a subset of sentences from the training corpus. Finally, they use these labelled sentences to build an anti-noise deep neural network for aspect and sentiment classification. Their experiments on two real data sets show the effectiveness of their model.

*3) MEJD:* Most of the current methods for ABSA independently distinguish the sentiment for aspects or targets, ignoring the corresponding relation between the targets and the aspects. Nevertheless, such a corresponding relation is significant for the accurate prediction of fine-grained sentiment polarity. To address the issue, Wu *et al.* [54] propose a novel end-to-end Multiple-Element Joint Detection model (MEJD). It can effectively extract all (target, aspect, sentiment) triples from a sentence. Specifically, they used BERT to obtain the embedding vector from the aspect-sentence joint and bidirectional long short-term memory to represent the sentence. Then, they use a convolutional graph network with an attention mechanism to capture the dependency between the body and the sentence. Their experiments show that on two restaurant datasets of SemEval 2015 Task 12 and SemEval 2016 Task 5, their model achieves state-of-the-art performance in extracting (target, aspect, sentiment) triples. Besides, the model also does multiple subtasks of target-aspect-sentiment detection well.

### *B. Unsupervised learning-based method*

*1) Expectation Maximisation-based method:* Most methods for aspect-based SA require a set of primary training or extensive linguistic resources, which makes them expensive and time-consuming in different languages. To address the issue, Shams, Khoshavi, and Baraani-Dastjerdi [56] propose a novel unsupervised aspect-based SA method called LISA. It firstly selects the preliminary polarity dictionary and the aspect word set as the representatives of the aspect. Then, it uses these two resources as the prior knowledge and feeds it to the unsupervised learning algorithm—the Expectation Maximisation algorithm to calculate the probability of any word according to the aspect and sentiment. Finally, it determines the aspects and polarities of any document in the aspect-level polarity classification. Their experiments show that on two datasets in the English and Persian languages, their method outperforms the baseline in aspect, opinion word extraction and aspect-level polarity classification.

*2) K-means based method:* To improve the accuracy of fine-grained sentiment classification of Weibo short texts, Tu and Yang [58] propose a method for micro-blog short text based on the PLSA model and K-means clustering model. First, they used PLSA to calculate the probability matrix between documents and topics, words and topics in the corpus. Then, they use the K-means algorithm to cluster the probability distribution of topic words and merge similar topics. Their experimental results show that their proposed method has higher classification accuracy than the PLSA model method alone.

### *C. Transfer learning-based method*

Transfer learning is an effective way to address the challenges related to the scarcity of data and the lack of human labels. And this is because it can find labelled data from relevant fields for training when the target field has fewer data, *i.e.*, it transfers the learned knowledge in an area to another [61]. Feng and Chaspari [62] recap fundamental concepts in the field of transfer learning and review work that has successfully applied transfer learning for SA. They also point out promising future research directions for transfer learning for improving the generalisability of SA systems.

For cross-lingual SA, the transfer learning-based method can evolve from one lingual knowledge to another. The fundamental challenge of cross-lingual learning for SA is that a source lingual has almost no overlap with the feature space of a target lingual. The translation of a source language into a target lingual faces several problems. One is to change the polarity of sentiments. For example, the English sentence “it is too beautiful to be true” means negatively: “it is not true because it is too beautiful”. However, when Google translates it into Chinese, it turns into a positive meaning: “it is so beautiful and true”. Another is that the vocabulary overlap between the documents translated into the target lingual, and the target document is very low.

Tao and Fang [57] propose a transfer learning-based multi-label classification method for aspect-based SA at a fine-grained level (*e.g.*, different features of products/services). Their evaluation experiment confirms that their method outperforms other mainstream multi-classification methods on online restaurant reviews.

### *D. TM based ABSA*

Yadav *et al.* [59]propose a human-interpretable learning method for ABSA, using the recently launched Tsetlin machines (TMs).They can realize interpretability by transforming the semantics of complex location-related text into binary form and mapping all features into bag-of-words(BOWs). They further use BOWs as the input of TM, so that they can learn aspect-based emotion patterns in propositional logic.Their experiments show how each relevant feature takes part in conjunctive clauses that contain the context information for the corresponding aspect word.At the same time, their accuracy is consistent with the existing neural network model.

### *E. Remark*

Table IV and Fig. 2 compare machines learning-based SA methods we brief in this section.

In Fig. 2, we show the accuracy, Macro-f1, precision and Recall of each model. Because some papers only calculate some of the evaluation criteria, we did not draw those not calculated in the figure. As shown in the figure, most papers have calculated accuracy, Macro-f1. However, on different data sets, each model performs differently, even quite differently. From Fig. 2, we can see that they rarely use standard data sets, which brings a certain degree of difficulty to the comparison of algorithms.

End-to-end ABSA explores to couple the BERT embedding component with various neural models and conducts extensive experiments.

MEJD proves the importance of bidirectional pre-training for language representation and shows that pre-training representation reduces the need for many carefully designed task-specific architectures.

CASC emphasises the contextual meaning of words and uses a semi-automated method driven by a mask language model to mark sentences. And it uses noise-robust loss function to train deep neural networks. Combining these two factors present a complete solution for the ABSA task.

LISA eliminates the disadvantage of the language specification method and proposes a general approach for different languages.

Transfer learning only needs small data to complete training, but it cannot be used in some fields. It requires a pre-training model with certain relevance.

Although the PLSA model and K-means(PLSAK) perform well in the paper’s problems, it has not been compared with other common algorithms.

TM based ABSA successfully provides a human interpretable learning approach for ABSA with comparable accuracy.

Diaz *et al.* [63] address age-related bias in SA. Most researchers use off-the-shelf tools to solve problems they face without considering the shortcomings of these tools unless they realise their faults in use. We may need to consider whether or not existing SA tools are biased (*e.g.*, ago, gender, and race). Dealing with these prejudices is necessary for proper SA.

When the data set is large enough, a Machine Learning (ML) based method for SA can achieve better classification results. However, its training requires a large amount of correctly labelled data, and the training time is long. And the size and structure of the data have a great impact on the effectiveness of an ML algorithm. So, due to the imbalance of categories in the data, the performance of the ML-based method for SA is often limited, which leads to underrepresented types often being classified incorrectly. ML-based methods rely on manual design and so are affected by human factors. Thus, such a method that performs well in one field may not necessarily perform well in another.

In the future, it is worth applying ML methods to do fine-grained SA of review texts with high-dimensional data characteristics. And it may need to study how different feature combinations impact the classifier's performance to find the optimal data feature combination. It may also be necessary to consider the multi-domain nature of a data set, mining implicit sentiments, particular sentence patterns such as negative sentences.

## V. Conclusion

Fine-grained SA is significant. This paper surveys the state-of-art of fine-grained SA compares the advantages and disadvantages of various fine-grained SA methods based on sentiment lexicon, machine learning, and deep learning. There are many open issues in fine-grained SA. For example, designing a unified method to simultaneously extract aspects, targets or attributes and predict sentimental polarity, transfer the rich public resources from coarse-grained SA to fine-grained SA, and capture the importance and influence between different modal data. Besides, multimodal SA issues and multilingual SA issues are both exciting topics worthy of further investigation in the future. In addition, pre-trained models may play an essential role in fine-grained SA tasks, so it is also worth studying in-depth.

## Acknowledgment

This work was supported by the National Natural Science Foundation of China (No. 61762016).

## References

[1] K. Coffman and A. Odlyzko, "Internet growth: Is there a "moore's law" for data traffic?" in *In: Abello J., Pardalos P.M., Resende M.G.C. (eds) Handbook of Massive Data Sets. Massive Computing*. Springer, 2002, pp. 47–93.

[2] M.-T. Hu, S.-W. Zhao, L. Zhang, and et al., "CAN: Constrained attention networks for multi-aspect sentiment analysis," in *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing*, vol. 1, 2019, pp. 4600–4609.

[3] G. Diaz, X.-M. Zhang, and V. Ng, "Aspect-based sentiment analysis as fine-grained opinion mining," in *Proceedings of the 12th Language Resources and Evaluation Conference*, 2020, pp. 6804–6811.

[4] S. Soumya and K. Pramod, "Fine grained sentiment analysis of malayalam tweets using lexicon based and machine learning based approaches," in *Proceedings of the 4th Biennial International Conference on Nascent Technologies in Engineering*, 2021, pp. 1–6.

[5] Q. Jiang, L. Chen, W. Zhao, and M. Yang, "Toward aspect-level sentiment modification without parallel data," *IEEE Intelligent Systems*, vol. 36, no. 1, pp. 75–81, 2021.

[6] C. R. Fink, D. S. Chou, J. J. Kopecky, and A. J. Llorens, "Coarse- and fine-grained sentiment analysis of social media text," *Johns Hopkins Apl Technical Digest*, vol. 30, no. 1, pp. 22–30, 2011.

[7] W. Nengsih, M. M. Zein, and N. Hayati, "Coarse-grained sentiment analysis berbasis natural language processing–ulasan hotel," *Jurnal Nasional Teknik Elektro dan Teknologi Informasi*, vol. 10, no. 1, pp. 41–48, 2021.

[8] M. I. Prabha and G. U. Srikanth, "Survey of sentiment analysis using deep learning techniques," in *Proceedings of the 1st International Conference on Innovations in Information and Communication Technology*, 2019, pp. 1–9.

[9] S. Tedmori and A. Awajan, "Sentiment analysis main tasks and applications: A survey," *Journal of Information Processing Systems*, vol. 15, no. 3, pp. 500–519, 2019.

[10] Y. Gao and S. Wang, "Application & comparison of several sentiment analysis platforms with open source review dataset," in *Proceedings of the 3rd International Conference on Computer Science and Application Engineering*, vol. 78, 2019, pp. 1–78.

[11] P. Lin and X. Luo, "A survey of sentiment analysis based on machine learning," in *Natural Language Processing and Chinese Computing: NLPCC 2020*, ser. Lecture Notes in Computer Science, vol. 12430, 2020, pp. 372–387.

[12] ——, "A survey of the applications of sentiment analysis," *International Journal of Computer and Information Engineering*, vol. 14, no. 10, pp. 334–346, 2020.

[13] P. Lin, X. Luo, and Y. Fan, "A survey of sentiment analysis based on deep learning," *International Journal of Computer and Information Engineering*, vol. 14, no. 12, pp. 473–485, 2020.

[14] X. Guo, W. Yu, and X. Wang, "An overview on fine-grained text sentiment analysis: Survey and challenges," in *Journal of Physics: Conference Series*, vol. 1757, no. 1, 2021, p. 012038.

[15] T. N. Prakash and A. Aloysius, "Textual sentiment analysis using lexicon based approaches," *Annals of the Romanian Society for Cell Biology*, pp. 9878–9885, 2021.

[16] B. Rojas, "Deep learning for sentiment analysis," *Language & Linguistics Compass*, vol. 10, no. 12, pp. 205–212, 2016.

[17] C.-Q. Jiang, Y.-B. Guo, and Y. Liu, "Constructing a domain sentiment lexicon based on chinese social media text," *Data Analysis and Knowledge Discovery*, vol. 3, no. 2, p. 98, 2019.

[18] Y. Gao, P. Su, H. Zhao, M. Qiu, and M. Liu, "Research on sentiment dictionary based on sentiment analysis in news domain," in *Proceedings of 2021 IEEE International Conference on Big Data Security on Cloud, High Performance and Smart Computing, and Intelligent Data and Security*, 2021, pp. 117–122.

[19] J. Rouces, L. Borin, and N. Tahmasebi, "Creating an annotated corpus for aspect-based sentiment analysis in swedish," in *Proceedings of the 5th Conference on the Digital Humanities in the Nordic Countries*, 2020, pp. 318–324.

[20] F. Bravo-Marquez, E. Frank, and B. Pfahringer, "Positive, negative, or neutral: Learning an expanded opinion lexicon from emoticon-annotated tweets," in *Proceedings of the 24th International Joint Conference on Artificial Intelligence*, 2015, pp. 1229–1235.

[21] M. Du, X. Li, and L. Luo, "A training-optimization-based method for constructing domain-specific sentiment lexicon," *Complexity*, vol. 2021, 2021.

[22] H.-T. Liu, J.-C. Zhu, X.-Y. Liu, G.-G. Li, Q.-M. Qian, N. Su, and N. Wang, "Expansion of sentiment lexicon based on label propagation," in *Proceedings of the 1 5th International Conference on Semantics, Knowledge and Grids*, 2019, pp. 145–152.

[23] Z. Ren, G. Zeng, L. Chen, Q. Zhang, C. Zhang, and D. Pan, "A lexicon-enhanced attention network for aspect-level sentiment analysis," *IEEE Access*, vol. 8, pp. 93 464–93 471, 2020.

[24] L. Yang, Y. Li, J. Wang, and R. S. Sherratt, "Sentiment analysis for e-commerce product reviews in chinese based on sentiment lexicon and deep learning," *IEEE Access*, vol. 8, pp. 23 522–23 530, 2020.

[25] O. M. Beigi and M. H. Moattar, "Automatic construction of domain-specific sentiment lexicon for unsupervised domain adaptation and sentiment classification," *Knowledge-Based Systems*, vol. 213, p. 106423, 2021.

[26] S. Li, W. Shi, J. Wang, and H. Zhou, "A deep learning-based approach to constructing a domain sentiment lexicon: a case study in financial distress prediction," *Information Processing & Management*, vol. 58, no. 5, p. 102673, 2021.

[27] R. Li, Z. Lin, P. Fu, and et al., "Emomix: Building an emotion lexicon for compound emotion analysis," in *Proceedings of the 2019 International Conference on Computational Science*, 2019, pp. 353–368.

[28] C.-H. Wang, K.-C. Fan, C.-J. Wang, and M. Tsai, "Ugsd: User generated sentiment dictionaries from online customer reviews," in *Proceedings of the 33rd AAAI Conference on Artificial Intelligence*, 2019, pp. 313–320.

[29] Turney and D. Peter, "Thumbs up or thumbs down? semantic orientation applied to unsupervised classification of reviews," *In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pp. 417–424, 2002.

[30] R. Y. Purba, "Analisis brand awareness dan sentiment analysis dengan media sosial twitter pada produk laptop di indonesia," Ph.D. dissertation, Institut Teknologi Sepuluh Nopember, 2021.

[31] B. Han, M. Han, and J. S. He, "Fine-grained sentiment analysis for customer review," *https://digitalcommons.kennesaw.edu/cs_etd/47*, 2021.

[32] N. Liu and B. Shen, "Aspect-based sentiment analysis with gated alternate neural network," *Knowledge-Based Systems*, vol. 188, p. 105010, 2020.

[33] H.-Y. Peng, L. Xu, L.-D. Bing, F. Huang, W. Lu, and L. Si, "Knowing what, how and why: A near complete solution for aspect-based sentiment

analysis," in *Proceedings of the 34th AAAI Conference on Artificial Intelligence*, 2020, pp. 8600–8607.

[34] K. Zhang, H.-F. Zhang, Q. Liu, H.-K. Zhao, H.-S. Zhu, and E.-H. Chen, "Interactive attention transfer network for cross-domain sentiment classification," in *Proceedings of the 33rd AAAI Conference on Artificial Intelligence*, 2019, pp. 5773–5780.

[35] L. Zhao, Y. Liu, M. Zhang, T. Guo, and L. Chen, "Modeling label-wise syntax for fine-grained sentiment analysis of reviews via memory-based neural model," *Information Processing & Management*, vol. 58, no. 5, p. 102641, 2021.

[36] Y. Tian, G. Chen, and Y. Song, "Aspect-based sentiment analysis with type-aware graph convolutional networks and layer ensemble," in *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 2021, pp. 2910–2922.

[37] Z. Lei, Y. Yang, M. Yang, W. Zhao, J. Guo, and Y. Liu, "A human-like semantic cognition network for aspect-level sentiment classification," in *Proceedings of the 33rd AAAI Conference on Artificial Intelligence*, 2019, p. 6650–6657.

[38] Z. Li, Y. Wei, Y. Zhang, X. Zhang, and X. Li, "Exploiting coarse-to-fine task transfer for aspect-level sentiment classification," in *Proceedings of the 33rd AAAI Conference on Artificial Intelligence*, 2019, p. 4253–4260.

[39] X.-Y. Ran, Y.-Y. Pan, W. Sun, and C.-J. Wang, "Learn to select via hierarchical gate mechanism for aspect-based sentiment analysis," in *Proceedings of the 28th International Joint Conference on Artificial Intelligence*, 2019, pp. 5160–5167.

[40] C. Sindhu and G. Vadivu, "Fine grained sentiment polarity classification using augmented knowledge sequence-attention mechanism," *Microprocessors and Microsystems*, vol. 81, p. 103365, 2021.

[41] N. Zhao, H. Gao, X. Wen, and H. Li, "Combination of convolutional neural network and gated recurrent unit for aspect-based sentiment analysis," *IEEE Access*, vol. 9, pp. 15 561–15 569, 2021.

[42] Z. Cao, Y. Zhou, A. Yang, and S. Peng, "Deep transfer learning mechanism for fine-grained cross-domain sentiment classification," *Connection Science*, pp. 1–18, 2021.

[43] H. Devamanyu, P. Soujanya, V. Prateek, K. Gangeshwar, C. Erik, and Z. Roger, "Modeling inter-aspect dependencies for aspect-based sentiment analysis," in *Proceedings of the North American Chapter of the Association for Computational Linguistic*, 2018, p. 266–270.

[44] A. Ghosh, P. Kotekal, and G. Chakraborty, "Attribute-based sentiment analysis in marketing: Application and strategic implications," *Model Assisted Statistics and Applications*, vol. 13, no. 4, pp. 311–318, 2018.

[45] B. Bansal and S. Srivastava, "Hybrid attribute based sentiment classification of online reviews for consumer intelligence," *Applied Intelligence*, vol. 49, no. 1, pp. 137–149, 2019.

[46] ——, "Context-sensitive and attribute-based sentiment classification of online consumer-generated content," *Kybernetes*, 2019.

[47] M. Pontiki, D. Galanis, J. Pavlopoulos, and et al., "Semeval-2014 task 4: Aspect based sentiment analysis," in *Proceedings of the 8th International Workshop on Semantic Evaluation*, 2014, pp. 27–35.

[48] A. Pablos, M. Cuadros, and G. Rigau, "V3: Unsupervised aspect based sentiment analysis for semeval2015 task 12," in *Proceedings of the 9th International Workshop on Semantic Evaluation*, 2015, pp. 714–718.

[49] M. Pontiki, D. Galanis, H. Papageorgiou, and et al., "SemEval-2016 Task 5: Aspect based sentiment analysis," in *Proceedings of the 10th International Workshop on Semantic Evaluation*, 2016, pp. 19–30.

[50] K. Cortis, A. Freitas, T. Daudert, and et al., "SemEval-2017 Task 5: Fine-grained sentiment analysis on financial microblogs and news," in *Proceedings of the 11th International Workshop on Semantic Evaluation*, 2017, pp. 519–535.

[51] C.-H. Wu, F.-Z. Wu, J.-X. Liu, and et al., "THU_NGN at semEval-2018 task 1: Fine-grained tweet sentiment intensity analysis with attention CNN-LSTM," in *Proceedings of the 12th International Workshop on Semantic Evaluation*, 2018, pp. 186–192.

[52] J. Anderson, "Sentim at semeval-2019 task 3: Convolutional neural networks for sentiment in conversations," in *Proceedings of the 13th International Workshop on Semantic Evaluation*, 2019, pp. 302–306.

[53] X. Li, L.-D. Bing, W.-X. Zhang, and W. Lam, "Exploiting bert for end-to-end aspect-based sentiment analysis," in *Proceedings of the 5th Workshop on Noisy User-generated Text*, 2019, pp. 34–41.

[54] C. Wu, Q. Xiong, H. Yi, Y. Yu, Q. Zhu, M. Gao, and J. Chen, "Multiple-element joint detection for aspect-based sentiment analysis," *Knowledge-Based Systems*, vol. 223, p. 107073, 2021.

[55] A. Kumar, P. Gupta, R. Balan, L. B. M. Neti, and A. Malapati, "Bert based semi-supervised hybrid approach for aspect and sentiment classification," *Neural Processing Letters*, pp. 1–18, 2021.

[56] M. Shams, N. Khoshavi, and A. Baraani-Dastjerdi, "LISA: language-independent method for aspect-based sentiment analysis," *IEEE Access*, vol. 8, pp. 31 034–31 044, 2020.

[57] J. Tao and X. Fang, "Toward multi-label sentiment analysis: A transfer learning based approach," *Journal of Big Data*, vol. 7, no. 1, pp. 1–26, 2020.

[58] S. Tu and B. Yang, "Research on sentiment classification of micro-blog short text based on topic clustering," in *Journal of Physics: Conference Series*, vol. 1827, no. 1. IOP Publishing, 2021, p. 012160.

[59] R. K. Yadav, L. Jiao, O.-C. Granmo, and M. Goodwin, "Human-level interpretable learning for aspect-based sentiment analysis," in *Proceedings of the 35th AAAI Conference on Artificial Intelligence. AAAI*, 2021.

[60] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," in *Proceedings of the 2019 North American Chapter of the Association for Computational Linguistics*, 2019, p. 4171–4186.

[61] V. M. Patel, R. Gopalan, and R.-N. Li, "Visual domain adaptation: An overview of recent advances," *Umiacs.umd.edu*, no. 3, pp. 53–59, 2015.

[62] K. Feng and T. Chaspari, "A review of generalizable transfer learning in automatic emotion recognition," *Frontiers in Computer Science*, vol. 2, p. 9, 2020.

[63] M. Diaz, I. Johnson, A. Lazar, and et al., "Addressing age-related bias in sentiment analysis," in *Proceedings of the 28th International Joint Conference on Artificial Intelligence*, 2019, pp. 6146–6150.

**Jie Liu** is a master student at Guangxi Normal University, China.

**Dr. Xudong Luo** is a distinguished professor of Artificial Intelligence at Guangxi Normal University, China. He published one book and more than 160 papers including 2 in top journal *Artificial Intelligence*, one of which has been highly cited by, for example, MIT, Oxford, and CMU research groups. Prof. Luo has international recognised reputation: co-chair and (senior) members of PC of more than 100 international conferences or workshops, including major conferences IJCAI and AAMAS, and referees for many international journals such as top journal *Artificial Intelligence*. He is also invited to make a presentation of his work in more than 10 universities internationally, including Imperial College. His research focus is on the areas of agent-based computing, fuzzy sets and systems, decision theory, game theory, knowledge engineering, and natural language process. Prof. Luo has supervised or co-supervised more than 40 master students, Ph.D. students, and research fellows.

**Pingping Lin** is a master student at Guangxi Normal University, China.

**Yifan Fan** is a PhD student at Soochow University, China.