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A Survey of the Applications of Sentiment Analysis

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Abstract—Natural language often conveys emotions of speakers. Therefore, sentiment analysis on what people say is prevalent in the field of natural language process and has great application value in many practical problems. Thus, to help people understand its application value, in this paper, we survey various applications of sentiment analysis, including the ones in online business and offline business as well as other types of its applications. In particular, we give some application examples in intelligent customer service systems in China. Besides, we compare the applications of sentiment analysis on Twitter, Weibo, Taobao and Facebook, and discuss some challenges. Finally, we point out the challenges faced in the applications of sentiment analysis and the work that is worth being studied in the future.

Keywords—Natural language processing, sentiment analysis, application, online comments.

I. Introduction

THE rapid development and popularity of the Internet inevitably lead to a significant increase in the number of online data [17]. Many of the data are about opinions that people express on public forums such as Facebook, Twitter, microblogs, blogs, and e-commerce websites. Particularly, online comment texts on e-commerce websites reflect the buyer's real feelings or experiences on the quality of the purchased goods, business services, and logistics services, regarding not only satisfaction information of consumers' shopping, but also their acceptance and expectation to new products or services. The insights into online comments significantly affect consumers' desires and decisions, which in turn impacts the efficiency of e-commerce platforms. Therefore, it is crucial to quickly mine and effectively take advantage of the comments. However, it is difficult to extract valuable information from these massive online texts. Therefore, the academic community and industry pay lots of attention to the issue [77].

Generally, sentiment analysis is to detect, analyse, and extract attitudes, opinions, and emotions expressed by people in a given dataset [36], [11]. So sentiment analysis is also called *opinion mining*, *orientation analysis*, *emotion classification*, and *subjective analysis*. Sentiment analysis tasks involve many problems in the field of natural language processing, including named entity recognition, word polarity disambiguation, satire detection, and aspect extraction. The number of problems involved in a sentiment analysis task is directly proportional to the difficulties users face in their application.

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The term of sentiment analysis was coined by Nasukawa and Yi [48], but it was Pang and Lee [49] who first proposed the task of sentiment analysis. They define the subjective calculation process of the text as sentiment analysis and opinion mining, yet they fail to give a more detailed definition of sentiment analysis. Later on, Liu [35] defines an emotional expression as a 4-tuple of (*Holder*, *Target*, *Polarity*, *Time*), where *Holder* means the opinion holder, *Target* refers to the object to be evaluated, *Polarity* stands for expressed emotion category, and *Time* is the evaluation time. Among them, the sentiment categories involved may vary with the sentiment analysis tasks. For example, in some sentiment analysis tasks, they are *positive* and *negative* only; in other tasks, they may be *positive*, *negative*, and *neutral*; or *happiness*, *anger*, *sorrow*, and *fear*; or just some scores (such as 1-6 points).

The sentiment analysis of online comments needs to consider the emotional polarity, emotional intensity, and sentimental polarity analysis. The main task of the analysis is to identify the subjective attitudes or opinions expressed by people, and the purpose of emotional intensity analysis is to define the intensity of the commenters' expressions range. Most studies treat sentiment analysis as a simple classification problem, but in fact, sentiment analysis is a massive suitcase research problem [12]. The reason for this is that sentiment analysis tasks need to solve many issues in the field of natural language processing, including named entity recognition, word polarity disambiguation, satire detection and aspect extraction. Each subtask is extremely important and faces unresolved issues. For example, for aspect-based sentiment analysis, if there are multiple opinion targets, if the aspect extraction sub-task is ignored, the accuracy of classification may be significantly reduced. The number of subtasks included in sentiment analysis tasks is directly proportional to the difficulties they face.

We can roughly sort comment texts into two types: objectivity comment texts and subjective comment texts. A piece of objective comment text is an objective statement regarding a certain thing, without any emotional colour, so it needs not to be analysed. A piece of subjective comment text is a subjective evaluation that a person has on a certain thing, such as his/her opinions, emotions, attitudes, and so on, and finally can conclude the meaning of derogatory polarity. Sentiment analysis can be used to summarise, reason, and analyse texts with subjective emotions in a certain way.

In terms of granularity, we can classify sentiment analysis into:

1) *Fine-grained sentiment analysis*, referring to the sentiment analysis of phrases and words. Word level is the basis and prerequisite for emotional tendency analysis. The premise of the words of text sentiment orientation analysis mainly refers to the

evaluation of the word extraction, and its emotional tendencies (commendatory/derogatory/neutral), strength (hate/disgust) sort. Attribute-level sentiment classification is a fine-grained sentiment classification task (i.e., given a comment and a specific attribute) for this particular attribute, the emotional polarity contained in the comment text is judged [57]. Wang et al. [71] has developed a system, which can get the best performance at the attribute level emotional classification task [65]. Aspect-based sentiment analysis is also a fine-grained sentiment analysis task, which aims to identify the sentiment polarity of a specified aspect in a sentence, such as Tay et al. [66].

2) *Coarse-grained sentiment analysis*, referring to the sentiment analysis of the overall propensity prediction of massive data sets at sentence level [69] and chapter level [74].
   - For a sentence-level task, a sentiment analysis system first judges whether or not a sentence is subjective. If it is subjective, then the sentence involves emotion and the system extracts the elements related to the emotional tendency from the sentence: the viewpoint holder, the evaluated object, the evaluation on the characteristics of the object (such as price, colour and performance), opinion words (such as *reasonable*, *bright*, and *excellent*), features, viewpoints (such as *colour* and *vivid*), and intensity.
   - For the chapter-level task, a sentiment analysis system needs to judge the embarrassing attitude of a certain text as a whole. Since a document often contains multiple objects evaluated (or multiple topics), the text-level sentiment analysis method is relatively rough, so it is difficult to apply to other tasks.
   - Massive information is also called multiple chapter-level information. The overall tendency of massive information prediction is to integrate and analyse the sentiment orientation information extracted from different sources for the same topic, and then to explore the characteristics of attitude and the trend. For example, by integrating online news and subjective comments on a product, the company can explore the public's overall attitude and trend toward the product.

Moreover, according to whether or not the emotion is determinable, Luo et al. [38] classify emotions as: 1) *explicit emotions*, referring to emotional texts containing obvious emotion words (such as *likes*), and 2) *implicit emotions*, referring to emotional texts that do not contain emotion words. For example, when a customer buys furniture, he says, "This table is covered with grey colour". A bit bleak, it is clear that the customer expressed dissatisfaction. Sometimes evaluation words lack the corresponding evaluation object, or the evaluation object is implicit. Therefore, Wang and Zhang [70] specifically use the method of automatic deep learning to identify implicit evaluation objects. Due to the difficulty of implicit sentiment analysis, the degree of dependence on background knowledge and common sense knowledge is relatively large. Hence, the current research mainly focuses on displaying sentiment analysis.

TABLE I
SENTIMENT ANALYSIS MAIN TASK

Classification	Level	Task
Fine-grained sentiment analysis	attribute	Identify and evaluate object attributes; attribute-oriented sentiment classification.
	aspect	Object recognition;aspect recognition; aspect-oriented sentiment analysis.
Coarse-grained sentiment analysis	sentence	Emotional information extraction; sentence polarity recognition.
	chapter	Sentence extraction; emotional information extraction; text polarity recognition.
	massive information	Recognition of polarities in various chapters; integration of emotional information in massive chapters.

Although some researchers have surveyed deep sentiment analysis, our survey in this paper is different from theirs. In 2019, Sasikala and Sukumaran [56] surveyed some methods of sentiment analysis based machine learning; Prabha and Srikanth [52] surveyed some methods of sentiment analysis at the sentence level and aspect level; Tedmori and Awajan [67] outline the main tasks and applications of sentiment analysis, but focus on surveying the classification and summary of the latest methods for sentiment analysis; Gao and Wang [22] compare the application of several sentiment analysis platforms with open source review dataset. In 2018, Zhang et al. [79] first gave an overview of deep learning and then surveyed the current applications of various deep learning methods in sentiment analysis comprehensively. In 2017, Soleymani et al. [58] surveyed some methods for multi-modal sentiment analysis. However, the above surveys focus on various methods for sentiment analysis. Rather, our focus in this paper is not on surveying sentiment analysis methods, but on various applications of sentiment analysis in various domains, and particularly we discuss the challenges faced by sentiment analysis in their applications and the future development direction.

The rest of this paper is organised as follows. Section II discusses the applications of sentiment analysis in online business. Section III particularly gives some application examples in intelligent customer service systems in China. Section IV examines some applications of sentiment analysis in offline business. Section V discusses some other types of applications of sentiment analysis. Section VI compares the applications on Twitter, Weibo, Taobao and Facebook, and discusses some challenges. Section VII summarises the paper and gives the outlook for the future.

II. ONLINE BUSINESS

This section mainly discusses some commercial applications of sentiment analysis, as summarised in Fig. 1.

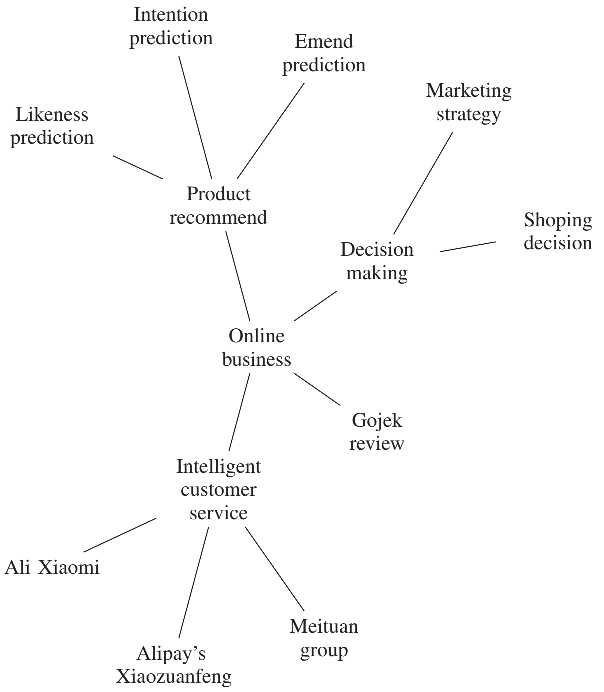

Fig. 1 Applications of Sentiment Analysis in online Business

A. Shopping Decision-Making and Business Strategy Formulation

Sentiment analysis has great potential in business applications. When consumers are shopping online, they make choices often according to the existing comments of other customers on the products. In fact, according to the report[1], 90% of consumers read reviews before visiting the company, while 88% of consumers trust these reviews with recommendations from acquaintances.

1) Merchant Strategy: Mohsen, Idrees, and Hassan [45] believe that consumers will consider the opinions or feelings of other customers before purchasing a specific product. Therefore, before buying a product, customers usually browse the relevant comments on the product and its sale volume, compare the comments on the same product in other stores, and finally make decisions according to their own needs. The merchant can apply the sentiment analysis technology to customers' comments to know which attribute (e.g., price, or style) of the product customer care more for each type of product.

2) Develop Targeted Marketing Strategies to Improve Product Quality and Service Quality: Customers' experiences could be utilised to enhance their items and administrations by measuring shoppers' remarks and criticism utilising sentiment analysis [2]. For example, the same product may be sold at different prices in different stores. If a shop sells a product at a higher price but is still highly praised and satisfied by customers, then other shops can increase their prices of the same product. The price increase will not bring unsatisfactory results to consumers but increase the profits of the merchants.

[1]https://www.invespcro.com/blog/

Similarly, if a shop's high price of a product causes terrible comments from customers, the shop needs to get its price down appropriately to retain consumers. Bad comments mean that consumers are dissatisfied with the product or its price.

Xia and Ding [72] propose a new method for Emotion-Cause Pair extraction. This method first extracts emotions, and the causes through multitasking, and then matches and filters the emotional causes. Their work digs out not only emotions but also the reasons, so that a merchant can adjust the sales strategy by knowing the cause of the consumer's feelings. Mohebollah and Maktoubian [44] use sentiment analysis technology to analyse tweets from four well-known brand laptops. Marketers can identify the advantages and disadvantages of products based on the popularity of various types of computers. Zhou et al. [84] use online review text sentiment calculation and fuzzy mathematics to study the online repurchase intention of online consumers. Jabbar et al. [30] propose a real-time sentiment analysis system for e-commerce applications, saving customers and service providers time for product evaluation. One of its limitations is that the system's built-in functions and support libraries are not rich enough to evaluate complex sentences and comments in different languages. It may be improved by using advanced machine learning methods or deep learning methods.

Carvalho et al. [13] apply sentiment analysis to rate online posts on Starbucks' promise of refugee hiring. From the results of emotion scoring, people can see that the pledge makes consumers more willing to spend on Starbucks. Otherwise, investors would reduce interest in Simbak investment.

Kauffmann et al. [33] show that the application of sentiment analysis can help in marketing decision making. That is, first analyse customer preferences based on star ratings and sentiment scores, then separate the positive and negative parts of reviews, and finally extract the main features of the product that introduce customers' negative or positive feelings, to assist marketing managers and consumers in their decision-making process. They improve the method of presenting data to users and visualised the data in a cloud. They suggest that other types of corpus can be used to verify their architecture in the future, and it is also worth studying how to filter out general functions that are not related to product performance.

3) Purchase Decision: Most researches pay more attention to how young people consume than to how the elderly consume, and explore little about what affects the consumption of the elderly. However, it is undeniable that the elderly are increasingly using online services or buying goods. So Helversen et al. [27] investigate how young people and older people use consumer reviews in hypothetical online purchase decisions, and studies how consumer reviews for older people and young people influence online buying decisions. On the other hand, the sentiment analysis method can help the sellers to understand which product attributes are highly concerned by consumers.

In the application in product review rating prediction [59], by understanding the customers' satisfaction with a product, the owners of an online shop can develop a good marketing strategy to generate product summaries based on the customers' common opinions. In the application of sentiment analysis in film and television drama, understanding the customers' joys and sorrows on the program can help to make good plot and online time. The comparative analysis of products (such as analysis and comparison of various clothing brands) can not only help businesses owners understand better the differences between these products in consumers' mind, but also help customers choose a suitable product.

B. Product Recommendation

Using sentiment analysis technology, a merchant can understand which attributes of a product are its consumers concerns, and accordingly recommend similar products to them to increase the transaction rate and save time and energy for consumers.

1) Recommended System: Recommendation systems can use sentiment analysis to fully consider the effect of online comments on user similarity and accordingly build an accurate user interest model [81]. If the users show a higher degree of similarity in their comments, it means that the interest between users is very similar. Also, the model can generate an intuitive feature explanation of why such a recommendation is made. The willingness and attitude that customers reflect in online commentary texts are often uncertain or ambiguous. To address the issue, Sun and Zhang [63] propose a sentiment analysis model based on uncertainty theory, and design a personalised recommendation algorithm. Their experimental results show that their algorithm improves the accuracy of recommendations and alleviates the problem of data sparseness.

Guo and Zhu [23] propose a user-based neural network model to represent the quantisation. The model fully uses implicit user behaviour feedback of having a better performance recommended, and user behaviour characteristics with a useful generalisation. Zhao, Huang, and Pan [82] study the differences in consumers' perceptions of various products and the key factors that cause differences, thereby improving the accuracy of recommending products to consumers. Their study reveals that consumers' emotion intensity and emotion weight on a product affect the overall performance of the product in the consumers' mind. This finding can be used to optimise product recommendation sequences.

2) Personalised Social Network Recommendation System: In social media, it is a difficult task to identify users' similarities [41]. To address the issue, Sailunaz and Alhajj [55] analyse the emotions and sentiment in Twitter posts, and use the analysis results to recommend users in the network who discuss similar topics or show similar feelings. Their work is an essential step toward a personalised social network recommendation system.

C. Gojek on Google Play Store

There are many online transport providers in Indonesia, such as Gojek, Grab, Uber, and My Blue Bird. Among them, Gojek is one of Indonesia's most popular online transportation service providers and has grown into an on-demand mobile platform and leading application that provides a full range of services including transportation, logistics, payment, and food delivery services. The Gojek application in the Google Play Store is one of Gojek's services. Users can download the GoJek app for free on the PlayStore. There are more than one million customer reviews in the PlayStore comment box. The comments are classified as positive, neutral (suggests) or negative (complaint or criticisms).

Sitaresmi et al. [24] analyse reviews in the Google Play Store, and use sentiment analysis technology to find user satisfaction, and to find out the level of service success, deficiencies and weaknesses of Gojek application. In their study, the data used are from the comments of Gojek on the Google Play Store. Firstly, they pre-prosess the data (cleansing, case folding, tokenising, filtering, stemming); secondly, they use naïve Bayes as the classifier to identify users' satisfaction and negative comments on the Gojek services. These studies can be used to evaluate the Gojek service basis and improve its service materials. In the future, it is worth looking at other aspects that may make users dissatisfied with Gojek services.

Day and Lin [19] explore the impact of deep learning on sentiment analysis on Chinese Google Play consumer reviews. They use Long-Short Term Memory (LSTM) deep learning models to conduct sentiment analysis on consumer reviews. Their experiments show that the accuracy of the LSTM-based sentiment analysis for Google Play consumer reviews reached 94%, outperforming the naïve Bayes and Support Vector Machine-based methods with respect to non-averaged sampled data.

D. Business Sentiment Analysis Platform and Software

There are also many software and platforms for sentiment analysis. Semantria for Excel[2] is a relatively mature emotion tool that can recognise emotions and visualise output data. The methods involved are speech marks and lexical links. IntenCheck API[3] is a powerful dictionary-based tool, mainly used for sentiment analysis and text analysis. It can classify the text polarity into positive, negative, and neutral. The IntenCheck API can also detect six main emotions: joy, surprise, anger, sadness, disgust, and fear. KNIME Analytics Platform[4] is open source software for data analysis. By using its open source extension, sentiment classification is based on learning models.

The software with the traditional method for sentiment analysis has the problem of low accuracy, so to equip them with deep learning based methods may be a promising direction of future research. Sentiment analysis software such as this should consider how to form a unified evaluation standard in the future. The current softwares can deal with texts only. In the future, it is worth extending them to analysing text, voice and, image at the same time.

III. Intelligent Customer Service in China

This section gives some application examples of sentiment analysis in customer service systems in China.

[2]https://www.lexalytics.com/semantria/excel
[3]https://www.intencheck.com/text-analytics-api/
[4]http://www.greenxf.com/soft/207097.html

A. Ali Xiaomi's Emotional Recovery Ability

The traditional customer service telephone customer service, where via the telephone, professional consultants answer questions from customers. There are several advantages to using intelligent customer service. First, intelligent customer service can autonomously talk to thousands of customers at the same time and detect the emotions expressed by them. For example, Majumder [39] propose the DialogueRNN system for sentiment detection in dialogue. Second, equipping intelligent customer service is a one-time investment, but can significantly reduce the number of employees. Third, no matter how unreasonable a customer is, the system can always treat the customer politely, so improving customer satisfaction and stimulating potential customers to reach a conclusion [73]. The further development direction of intelligent customer service includes not only making as simple as consulting, but also enabling it to buy airline tickets, charge bills, do shopping guides (such as Alibaba's Ali Xiaomi), and even function as personal assistants.

The essence of intelligent customer service is an agent. Previously, emotions are a gap that humans and machines cannot cross. For human-computer interaction, emotion and perception are the most critical capabilities [75]. Today's agents already can have humanoid emotions, i.e., the emotional agent. The so-called emotional agents use artificial methods and techniques to give agents human-like emotions. That is, it can express, recognise, understand, imitate, extend and expand human emotions [31]. Intelligent agents have been used in the customer service systems of many Internet giants such as Taobao, Jingdong, Netease, and Tencent. Such agents make real money for and significant benefits to major businesses.

The original version of Ali Xiaomi cannot process emotions, it can just answer questions in the high-frequency scene. For example, if a customer asks for a refund of goods and says "hurry up to refund me", the response of Ali Xiaomi is a textual instruction about how to return the goods. Although we can see that the customer is emotional, Ali Xiaomi cannot understand the emotion. Later on, Ali Xiaomi became an intelligent customer service that can understand the customer's emotions and imitate the human expression of their emotions. For Alibaba, Ali Xiaomi, the intelligent customer service, creates unpredictable value. In fact, during the annual Double Eleven Shopping Festiva every year, Ali Xiaomi helps bring immense benefits to Alibaba.

There are many kinds of human emotions, customers can swear, but artificial customer service and service agents should not do so. Moreover, customer service should not show some emotions, such as abuse, irony, or sarcasm. However, service agents can express some emotions, such as happiness and grievances. Ali's research team divides emotions into 38 categories as follows: gratefulness, surprise, disappointment, sorry, expectation, doubt, jealousy, happiness, anxiety, resentment, dislike, depression, grievance, contempt, fear, loneliness, anger, sadness, satisfaction, boredom, compassion, calm, worry, excitement, mind, remorse, shame, resentment, hesitant, thinking, moving, admiration, palpitation, depression, pride, a guilty conscience, envy, and abuse. But Ali Xiaomi only uses the most common seven classes: grievance, fear, anxiety, disappointment, anger, insult, and thanks. The model trains a separate classification model, which makes the emotion classification of these seven more accurate. For related questions about how Xiaomi can do generative language chat, please refer to Song et al. [61].

TABLE II
AN EXAMPLE THAT XIAOMI COMFORTS A CUSTOMER

Role	Dialogue
Customer:	The weather is very good today.
Xiaomi:	Yes, the seven-star district is just a little bit cloudy today, but a temperature of about 26 degree Celsius is perfect.
Customer:	I bought a piece of clothing last week. It is a broken one. I was sad when I saw it. I have been waiting for a long time for a replacement.
Xiaomi:	Madam, really embarrassed for letting you down. Xiaomi can understand your feeling on this matter. Don't be angry, please!
Customer:	I have asked for a replacement. Please deliver it to me quickly. I need it urgently.
Xiaomi:	Madam, don't worry. Xiaomi will help you.
Customer:	Double eleven logistics problems. I am particularly afraid that my courier will be burned or dropped in the waterway.
Xiaomi:	Madam, Xiaomi is here. Don't worry so much. We will do our best to protect your rights and interests.
Customer:	I have been waiting for such a long time but have not received the goods yet. I am so disappointed.
Xiaomi:	Madam, very sorry for what you are experiencing right now. Xiaomi must work harder to make you satisfied.
Customer:	I won't buy clothes here, logistics is very slow, poor attitude, poor quality, furious.
Xiaomi:	Madam, very sorry for your unpleasant shopping experience. Please forgive us.
Customer:	You make me tired. You can't solve any of my problems. How stupid you are! Why are you here?
Xiaomi:	Madam, I know something wrong happened to you, but You'll be fine. Xiaomi is trying her best to help you.
Customer:	Solve my problem as soon as possible. Thanks.
Xiaomi:	My pleasure. Thank you for your trust in me.

Ali Xiaomi uses the most commonly used seven classes of emotion words to comfort customers emotionally. To appease the customer's emotions, Ali Xiaomi first uses sentiment analysis to identify the emotions of customers, then classifies these emotions, and finally responds accordingly. For example, when a customer says that she is in a good mood today, the system responds happily. The rules for generating a happy response can be set up manually. For example, when a customer expresses pleasure, the agent should be happy as well; when the customer is insulted, the customer service expresses sympathy to the customer. The dialogue in Table II and Table III reflect Xiaomi's sympathy, anxieties, fears, disappointments, anger, insults, and thanks to seven kinds of emotional resilience.

At present, Ali Xiaomi still has some problems with recognising weak emotions. For example, if the customer says, "Your answer makes me very uncomfortable", Xiaomi can only say, "Xiaomi is still in learning and can't understand what you said." Ali Xiaomi can only recognise emotions in text and reply in writing. They have not considered Xiaomi's speech interaction with customers. In the future, it is worth studying multi-modal emotion recognition of text, audio, image, and

TABLE III
A DIALOGUE OF XIAOMI WITH AN ANGRY CUSTOMER

Role	Dialogue
Customer:	Hello!
Xiaomi:	Hello! What can I do for you? Just tell me, please!
Customer:	I ordered some fruit yesterday. I am worried that it may rain soon. Please deliver it to me very very quickly.
Xiaomi:	Madam, very sorry for the delay. Please choose the order that can delivere goods quickly.
Customer:	Can you ship it quickly?
Xiaomi:	Don't worry, madam, Xiaomi understands your feeling now.
Customer:	I have already had to chase my purchase twice. I will be furious if I can't have it in time.
Xiaomi:	Madam, I am so sorry for this. Xiaomi fully understands your feeling. If it was Xiaomi, Xiaomi would be angry too. But anger is not good for me anyway. Xiaomi will help you to see what solution you can have. We will clear this up for you first.
Customer:	The fruit is here. Most of them are ruined, too disappointing.
Xiaomi:	I really can't help you. I am still in learning.

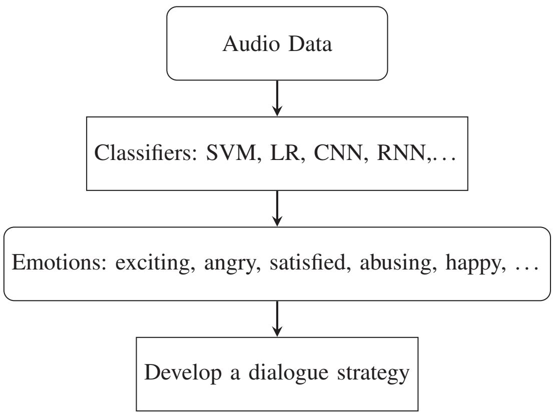

Fig. 2 Audio Data Emotion Recognition

video.

B. Intelligent Customer Service of Other Platforms

1) Emotional Recognition of the Meituan Group: The Meituan group tries to identify the emotions in audio data and develops a dialogue strategy based on the detected emotions. The biggest challenge here is the weakly labeled training set [34], as shown in Fig. 2. The research team of the Meituan group has now realised the emotional recognition of audio through weak label learning. One of the future research studies is to realise the emotion recognition of speech and text multimodality. The company's team of intelligent customer service will continue to study multiple rounds of context modelling (intentional understanding), allowing users to make multiple-choice questions (intended recommendations), speech and text multimodality (emotion recognition), historical topic extraction, segmentation (seat assistant), and so on.

2) Alipay's Xiaozuanfeng: Xiaozuanfeng is Alipay's intelligent customer service. For colloquial questions, it is difficult for intelligent customer service based on search engines to give *smart* answers. The most significant advantage

TABLE IV
A DIALOGUE OF LITTLE DIAMOND WITH A CUSTOMER

Role	Dialogue
Customer:	I bought a coat online last time. It was my friend who helped me pay with Alipay, but I returned the purchase.
Xiaozuanfeng:	Perhaps your question is related to the following options, please click on one of the options below.
Customer:	I mean, I need a refund, but the money has not been returned to my friend's account. What should I do?
Xiaozuanfeng:	Sorry, I can't understand your question. I am still learning.
Customer:	You are really stupid! Useless.
Xiaozuanfeng:	Sorry, can you try to ask me in a different way. Then I might be able to answer your question correctly.
Customer:	What should I do if we never get the refund?
Xiaozuanfeng:	According to your payment method, the time for the refunding process is different. If your friend paid using Ant Credit Pay, the refund process can be completed immediately.
Customer:	You still haven't solved my problem. It's too irritating.
Xiaozuanfeng:	Can you have a look at the following instructions? Maybe it is helpful.

of Xiaozuanfeng is that it can learn by itself. That is, the more questions it answers, the more accurate its answers are.

From the dialogue between the customer and Xiaozuanfeng in Table IV, we can see that the answer style of Xiaozuanfeng is guiding the user to clarify the problem or giving a choice answer and method. Xiaozuanfeng can identify a customer's abusive feelings and appease the customer, but cannot detect other emotions. Alipay's intelligent customer service agent comes with an intent mining system called AntProphet [15]. AntProphet can quickly respond to a user's first question, quickly collect the user's profile, historical behaviour trajectory, and context information to predict the potential problem that the user wants to solve. Because of AntProphet's Alipay customer service system, the overall rate of customers' satisfaction with Alipay exceeds 85%.

In addition, Taobao e-commerce website[5], Jingdong e-commerce website[6], Tmall supermarket (shopping)[7], 58 city[8] (for house renting and job hunting), Vipshop[9], and other platforms have also enabled intelligent customer service, making huge profits for these companies. Qiangdong Liu, Jingdong's CEO, say that his company has been developing an artificial intelligence customer service in past six years, and now over 50% of its services are done by computer systems[10]. Especially when customers use online communication tools, 90% are artificial intelligence technologies.

Generally speaking, computer customer services should have human emotions to make online communication easier and natural, and make users feel better. Mobile assistants often used in daily life (such as QQ Xiao Bing of Tencent and Siri of Apple) have weak abilities of emotion.

[5]https://www.taobao.com/
[6]https://www.jd.com/
[7]https://chaoshi.tmall.com/?targetPage=index
[8]https://gl.58.com/
[9]https://www.vip.com/?wxsdk=1
[10]http://finance.eastmoney.com/news/1354,20180517873498620.html

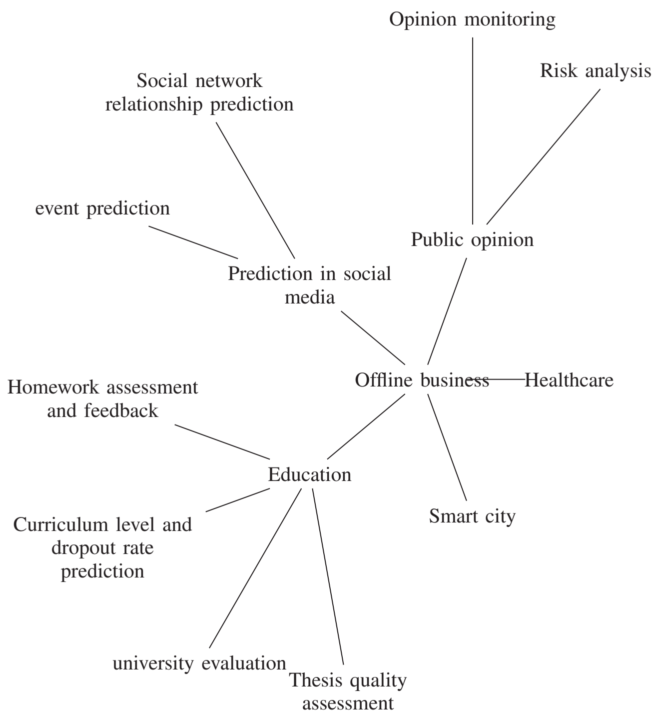

Fig. 3 Applications of sentiment analysis in offline business

The role of intelligent customer service is not limited to consulting tasks or after-sales business, but more to facilitating transactions (i.e., to promote the success of business negotiations). The ultimate goal of a negotiation is to reach a specific agreement [37]. A negotiation is not just a war of words in the form of expression, but also a psychological war [78]. If the customer service wants to facilitate the transaction, it is necessary to read a customer's mind and accordingly convince them to buy happily. To read minds includes reading emotions or guessing emotions, so that customer service requires the clever use of psychological strategies to win the ultimate success of the negotiations. For example, the customer said, "I am in desperate need of a shoe shelf at the moment. The shoes at home are so messy." Then customer service should be able to judge the person's anxious emotions and rush to reach a deal to solve the current problems. If the customer said: "When I received the fruit, it was already ruined. It was not fresh at all. It's too bad!", the system should realise that the customer had a disappointing feeling about the previous shopping experience. At this time, if the customer service system wants to hold this customer, it has to go to a psychological war to make up for the bad feelings brought by the last transaction. A psychological war during negotiations is also a sentiment analysis war.

IV. Offline Business

This section mainly discusses some non-commercial applications of sentiment analysis, as summarised in Fig. 3.

A. *Public Opinion Monitoring and Risk Analysis*

The development of the Internet has enabled people not only to get news quickly but also to express their opinions publicly and participate in commenting on events. Publishing public opinions online is not limited by time and space. Anyone who can surf the Internet can express their own opinions online. Since the subjects of online public opinions are uncertain, anyone can become the main body of online public opinions. Also, people often comment online after an incident, if more people pay attention to this incident, that online public opinions likely develop at an immeasurable rate. Therefore, the impact of online public opinions on the government and society is growing. This influence could be positive and negative. Positive ones can expand the influence and enhance the image of the government. Those wrong public opinions (such as leaking state secrets, provoking national incidents, and inciting people's negative emotions) will bring public opinion pressure and even crisis to governments. It threatens the authority of the government, the stability of the state, and a better society. It is a challenge for a country and its government to cope with the substantial public opinion storm that can form in a short period of time.

1) Risk Analysis: Zhang et al. [80] use sentiment analysis techniques and the principle of minority obeying majority to predict Weibo public opinions. Applying sentiment analysis to tweets related to a trending topic can also identify whether or not people are talking positively or negatively about it, thus providing important information for real-time decision making in various domains. For example, Maria et al. [40] propose SentiTrend, a system for trend detection on twitter and its corresponding sentiment analysis. Mertiya and Singh [43] use tweets related to movie reviews as the data set and merger naïve Bayes and adjective analysis for finding the polarity of the ambiguous tweets. The results reach the accuracy of 88.5%. Generally speaking, through sentiment analysis, a company can quickly understand people's general opinion trends on popular products, achieve effective prevention and response to various public opinion crises, pay attention to public opinion risk assessment, and prevent and reduce public opinion risks in the first place.

2) Opinion Poll: Do customers express their opinions? Are customers' opinions consistent with a company's interests? If they are inconsistent, what is the difference? How to detect this kind of opinion from social media? It can be seen that another major application of sentiment analysis technology is the public opinion monitoring [14].

a) Public opinion: Zheng et al. [83] discuss the most important part of public opinion monitoring when predicting public opinion. From the perspective of a company and its managers, the United Nations has developed Global Pulse 7 for global emotional fluctuation monitoring. The research team of Beijing University of Aeronautics and Astronautics has launched MoodLens 8, the first online emotion system for Chinese microblogs. In the domain of elections and political issues, Romney and Obama launched a fierce publicity campaign on Twitter in the U.S. elections of 2012; an analysis of sentiments on Facebook during the 2016 U.S. presidential election [6]. It influenced ordinary people and journalists and became a typical case of Internet participation in presidential election campaigns.

b) Satisfaction with community living environment and quality: By analysing the semantics and sentiment of online neighborhood reviews in residential communities, learning how people think about their living environment. People's perception of the community indicates their satisfaction with the living environment and quality of life. Huet al. [28] analyse the comment data of the residential community, and more accurately analyse the topics people talked about in the comments and their neighbors in different aspects emotion. Their research results can also be used to support research on urban planning and quality of life.

c) Hotel satisfaction: Airbnb's popularity and influence in the tourism and hospitality industries has increased year by year. Cheng and Jin [16] analyse online reviews of a large number of Airbnb users. Their investigation is dedicated to solving the problem raised by Tussyadiah and Zach [68], which is to use sentiment analysis technology to identify positive and negative opinions of Airbnb users. According to the results of their survey, Airbnb users tend to evaluate their current accommodation experience based on their previous accommodation experience. The three key factors affecting Airbnb's user accommodation experience are location, facilities, and landlord, but price is not the key factor. The main reason for negative reviews from Airbnb users is that the accommodation environment is noisy. This research will help the tourism industry and hotels to improve service quality. Future research will consider the impact of different cultural backgrounds on user accommodation mood.

B. Education

People's learning process involves cognition and emotion. The main goal when performing sentiment analysis in the education field is to discover the negative emotions of students, and to adjust teaching methods in a timely manner before students are affected by negative emotions.

1) Predicted Dropout Rate: Dolianiti [20] summarises the four major applications of sentiment analysis in education: instruction evaluation; institutional decision-making or policy making; intelligent information or learning system enhancement; and homework evaluation or feedback improvement. They also suggest to use sentiment analysis to study the correlation between emotions and curriculum levels, dropout rates, and the correlation between students' emotions and performance, and predict whether or not students will drop out in the next week. In addition, the research studied cross-course sentiment classifications as in [8], i.e., training on one course and testing on the other. Their research focuses on data sets in the field of education, which has field limitations. However, the loss caused by domain knowledge is unavoidable, and the impact of knowledge in different domains is prominent. For example, social media has special terms and common irony words in the political field, which shows that there is no way to use a unified standard solution to solve sentiment analysis tasks in different fields. As a result, the domain limitations of sentiment analysis tasks are inevitable.

2) Student Comments on Universities, Teachers and Teaching: Questionnaire surveys are the most commonly used method in the evaluation of education in colleges and universities. Many researcheres use sentiment analysis techniques to analyse student comments, such as evaluating a teacher [7]. Colace, Santo and Greco [18] collect the texts of students' discussing information about technology courses from Moodle forums and chats. They use sentiment analysis techniques to analyse students' opinions and attitudes about the classroom. Their research results show that if the contents and methods of teaching are adjusted according to the emotions expressed by students, then students are more active in the classroom. Hence, by analysing the feedback from the emotional mining of the feedback generated by the students, educators can better meet their needs and expectations. Similarly, Janssen et al. [32] use sentiment analysis technology to analyse the user's evaluation and feedback on a university in social media; Patel et al. [50] use sentiment analysis technology to evaluate parents' feedback on universities in parent meetings.

3) Assess the Quality of the Paper: Burstein et al. [10] propose the use of sentiment analysis to evaluate the quality of students' papers, because the construction of arguments in the papers depends on the existence of opinions and emotional statements.

4) Future Work: In the future, it is worth paying more attention to the data generated in the real-world teaching environment, such as student classroom forums, and opinions expressed in the classroom. Students' different communication styles and language expressions in communication are also challenges to sentiment analysis tasks, which is worth pondering. In addition, different subject areas and curriculum contents may cause data diversity, which is also a big challenge.

C. Medicine

Sentiment analysis is increasingly used to analyse people's emotions, but a major drawback of current sentiment analysis methods is the lack of aspect-level granularity improvements, and so it is rarely used in online knowledge communities. The medical knowledge community is an open platform that can access medical resources and share medical knowledge and treatment experience, so it is necessary to find a method of emotion classification in the medical knowledge community.

1) Online Medical Knowledge Sharing: Under this consideration, Gan et al. [21] propose an adaptive learning emotion recognition method based on mutual information feature weights. For feature extraction, they choose the mutual information method because the method can capture the correlation and redundancy of features. Their experimental results show that this method has better performance in identifying redundant features of low-frequency words in the online medical knowledge sharing community.

Compared with applications in other fields, there is less research on sentiment analysis in the medical field, and sentiment analysis in the medical knowledge sharing community is still relatively lacking. Information receivers in the medical knowledge sharing community pay attention to the sentiment polarity expressed in comments, but need to pay more attention to the intensity of sentiment words in comments or overall evaluation. On 4 February 2020, the Science and Technology Department of the Ministry of Industry and Information Technology of the People's Republic of China propose to make full use of the power of artificial intelligence to work together to combat the pneumonia epidemic of the new coronavirus infection. With the help of sentiment analysis technology, we can monitor the psychological changes of the people, monitor the trends of public opinion, and soothe the people's emotions in real time.

D. Smart City

Smart city refers to the use of various information technologies or innovative ideas to integrate the city's constituent systems and services to improve the efficiency of resource utilisation, optimise city management and services, and improve the quality of life of citizens. The construction of a smart city requires four core technologies: internet of things, cloud computing, artificial intelligence, and 5G. As a technology of artificial intelligence, sentiment analysis plays an important role in the construction of a smart city.

Alam et al. [5] study sentient analysis on social media through parallel dilated convolutional neural network for smart city applications. They argue that smart city applications can take advantage of social media sentiment analysis to collect and process social data from Facebook and Twitter to check people's views on smart cities. All in all, their sentiment analysis based on tweets has helped smart city applications, enhancing people's understanding and perception of smart cities.

V. Other Types of Application

In this section, we discuss some types of the applications of sentiment analysis.

A. Relationship and Event Prediction

1) Social Network Relationship Prediction: Interpersonal relationship analysis is to predict the relationship between people in the social network or potential connection between two unrelated persons in the future (e.g., marriage, colleagues, friends, strangers, and relatives). Because social relationships are relevant to contents and structures in the network, people with the same or similar behaviors or characteristics may have common hobbies and interests [42]. Tan et al. [64] use network information to study potential common interest prediction problems. If a person is represented as a node and his/her relationship with others as a link in the network, the relationship prediction is converted into a link prediction problem.

2) Predictive Analysis of an Event: For example, Little-AI (Alibaba Cloud's artificial intelligence system) successfully predicted Wen Li's victory in the program "I am a singer" according to on-site data and comments on social networks. Before this, Little-AI had accumulated a lot of practical experiences for prediction. For example, for the transport sector it helps to predict future road congestion situation. On 6 April 2016, at the final of program "I am a singer", Little-AI successfully predicted the road congestion in Changsha city. Besides, Little-AI helps AliMusic predict dark horse music, and so on. Other effective applications of sentiment analysis include movie box office forecasting [29], review rating forecasting [59], and stock market forecasting [54].

B. Dialogue System

The applied research of sentiment analysis in dialogue is becoming a new research frontier. Recently, Poria et al. [51] study emotion recognition in dialogue. They list the relevant challenges, datasets and cutting-edge methods of emotion recognition in dialogue. In particular, the main challenge of emotion recognition in dialogue systems are to classify the types of emotions, annotate the basis of emotion, model dialogue context, model speaker-specific, model listener-specific, deal with emotion transfer phenomena, recognise fine-grained emotion, set counterpart dialogue, handle satire phenomenon, and emotionally reason. Commonly used data sets are IEMOCAP and SEMAINE.

1) CMN: Hazarika et al. [26] propose Conversational Memory Network (CMN) for emotion recognition in dyadic dialogue videos. CMN is the first method that uses the speaker's specific context memory (speaker's vocalisation history) to identify emotions in a conversation. It is used for emotion detection in binary conversation videos. Of course, CMN can also be extended to multi-party conversations. CMN is capable of modelling speaker-based emotions, but in some cases, the CMN model may fail, for example, in the absence of historical discourse.

2) ICON: Hazarika et al. [25] propose the Interactive Conversational Memory Network (ICON). ICON is an improved method of CMN. ICON not only considers the history of each speaker's vocalisation, but also models the emotional impact between each speaker hierarchically as a global memory. In the future, it is worth extending ICON to multi-party conversations, testing ICON on other relevant conversation-based applications, and using it to generate empathy conversations. In addition, it is also interesting to apply ICON to other dialogue data sets to evaluate its versatility.

3) DialogueRNN: Majumder et al. [39] propose an attentive Recurrent Neural Network (RNN) for emotion detection in conversations, which they called DialogueRNN. DialogueRNN pays attention to the information of the speaker. Like ICON, DialogueRNN also models the emotional impact between speakers. The difference is that DialogueRNN is a multi-stage hierarchical modelling. At the same time, it integrates the attention mechanism and uses RNN modelling. On data sets IEMOCAP and SEMAINE, DialogueRNN performs better than CMN and ICON because of better context representation. Future work is to extend the method to a multi-party setup with more than two speakers.

TABLE V
APPLICATIONS ON TWITTER, WEIBO, TAOBAO, AND FACEBOOK

Research	Data Sources	Topic	Emotion Category	Performance
Carvalho et al. [13]	Facebook	Starbucks pledges to hire refugees	Sadness, joy, fear, disgust, and anger	Acc: 72.64%
Mohebollah et al. [44]	Twitter	Apple, Dell, Lenove, HP four brand notebook computers	Positive and negative	-
Zhou et al. [84]	Taobao	Five sportswear brands in Taobao	Satisfaction,trust	-
Song et al. [60]	Taobao	Review rating prediction	IMDB; 1-10 points; Yelp13 and Yelp14: 1-5 points.	Acc: 87.89%; F1: 70%
Sailunaz et al. [55]	Twitter	Any topic	Anger, disgust, fear, joy, sadness, surprise and neutral	Acc: 66.86%
Majumder et al. [39]	Dialogue or speech	Actorsperform improvisations or scripted scenarios	IEMOCAP: happy, sad, neutral, angry, excited, frustrated; AVEC: valence, arousal, expectancy, power	Acc: 69.2%; F1: 62.9%
Zhang et al. [80]	Weibo	Any topic	20 fine-grained emotion classes	Acc: 88%; F1: 89%
Mertiya et al. [43]	Twitter	Movie reviews	Positive and negative	Acc: 88.5%
Alashri et al. [6]	Facebook	The 2016 U.S. presidential election.	Positive, negative, and neutral	-
Day et al. [19]	Google Play	Chinese Google Play consumer reviews.	1-5 points	Acc: 94%

TABLE VI
APPLICATIONS ON HOTEL, MOVIE, RESTAURANT, AND TOURISM

Research	Specific Field	Method	Language	Emotion Category	Performance
Mostafa et al. [46]	Hotel	NB	Chinese	Good and bad	Acc: 85%; Precision: 0.76; Recall: 0.67
Al-Smadi et al. [3]	Hotel	SMO (SVM Weka implementation)	Arabic	Positive and negative	Acc: 95.4%
Qawasmeh et al. [4]	Hotel	RNN vs SVM	Arabic	Positive and negative	Acc:RNN-87%;SVN-95.4% F1:SVM-90%; RNN-49%
Chen et al. [16]	Hotel	Big data	English	Positive and negative	-
Devi Bodapati et al. [9]	Movie	LSTM	English	Positive and negative	Acc: 88.46%
Rehman et al. [53]	Movie	CNN-LSTM	English	Positive and negative	Acc: 91%
Mertiya et al. [43]	Movie	NB	English	positive and negative	Acc: 88.5%
Nakayama et al. [47]	Restaurant	-	English and Japanese	Favorable (45 stars) and critical (12 stars)	-
Sun et al[62]	Restaurant	KNN	Chinese	positive and negative	-
Aguero-Torales et al. [1]	Restaurant	Software tool; cloud	English	positive, negative or neutral	-

4) IANN: Yeh, Lin, and Lee [76] propose an Interactive Awareness Attention Network (IANN) for speech emotion recognition in speech dialogues. IANN uses internal speaker relationship modelling. Similar to ICON and CMN, IANA utilises each speaker's independent memory modelling and incorporates contextual information into speech expressions through an attention mechanism to solve the problem that the emotion-related information embedded in the current discourse is not explicitly learned and integrated into the representation of the current discourse. The author believes that neutrality is irrelevant to the context. In the future, it is worth studying how to formulate a strategy that also considers the nature of emotion categories.

All of the above models confirm that the context history and interpersonal effects are useful for emotion recognition tasks in dialogue. Not only can the adjacent sentences contain a lot of context information, but if future sentences are used as context, it should also bring benefits to the model. CMN and ICON do not use future sentences as context. However, real-time applications such as negotiation cannot rely on future sentences, so the benefits of future sentences are only theoretical. All four methods could be extended to multi-party dialogues in the future.

VI. DISCUSSIONS AND CHALLENGES

From online business to medical care, tourism, hospitals, education, social activities, and even political elections, applications or products related to sentiment analysis have appeared in almost all fields. In the future, we can continue to explore applications in the above-mentioned fields, and pay more attention to unapplied fields. The current technology is still heavily dependent on the quality of the input data, which means that recognizing the double meaning of text, jokes or innuendos is a difficult task for sentiment analysis. Some researchers are also working on building a general data set, hoping to reduce the workload of data input while also achieving the same effect as a specific field data set.

Table V compares the appilcations of sentiment analysis on Twitter, Weibo, Taobao, and Facebook, and Table VI compares the applications on specific fields such as Hotel, Movie, Restaurant, and Tourism. In both the tables, an empty cells (-) means that the value is not required for the task evaluation measure or the approach has no reported results.

VII. CONCLUSIONS AND FUTURE WORK

This paper surveys the various applications of sentiment analysis in business, intelligent customer service, public opinion mining and risk analysis, education, medical care, smart city, relationship and event prediction, and dialogue systems. We also discuss some software tools of sentiment analysis and cases. Finally, we compare some applications and point out the challenges in the application and the future development direction.

In particular, the applications of sentiment analysis on non-English texts and available resources are still relatively few. For sentiment analysis on non-English texts such as Arabic, Spanish, and Chinese, it is worth to pay more attention to explore.

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