A Faceted Characterization of the Opinion Mining Landscape

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***Abstract*—Increasing amounts of user generated content (UGC) on the Internet, is creating research interest in opinion mining. This involves automatic detection of opinions about products, services, political parties, celebrities and events from user generated content. Research efforts in opinion mining are thus far, fragmented and have followed several approaches. However, most of them require understanding of domain-specific opinion words and their polarity, and language-specific opinion rules. In addition, semantic constructs like sarcasm pose open challenges. In this paper, we try to characterize the opinion-mining landscape by proposing a faceted taxonomy of the different aspects of opinion mining. We then survey literature and place these in appropriate places in the proposed model. We also propose a general purpose workflow required from any opinion mining engine. Finally, we speculate on specific challenges in the opinion mining landscape.**

Keywords: Opinion Mining, Sentiment Analysis, Survey

I. Introduction

Text documents contain knowledge which can be broadly classified in two categories: *facts*, which are typically objective statements about some entity or event; and *opinions*, which are subjective in nature expressing sentiments and feelings of the author about the entity. Both facts and opinions are important for decision making. People would want to know others' opinion before taking a decision, while corporates would like to monitor pulse of people in a social media about their products and services and take appropriate actions.

Initial research in text mining [3], [6], [10], [23], [25] focused on extracting factual information from documents. In recent times, focus is shifting towards opinion mining – also called *sentiment analysis*. One of the drivers for this shift is availability of opinionated text in the form of reviews, blog posts, social media comments and more recently, tweets. Such documents are also called *User Generated Content* (UGC).

Opinions expressed in UGCs are challenging to extract because of complications like the latent context in which an opinion is expressed. The reader of the content needs to make a *mental model* for the context to understand the content and infer the opinion. Another challenge posed by UGCs is the author's identity. Opinions are subjective in nature, and the trust and credibility assigned to an opinion depends on *who* is giving the opinion and what is their motivation in publicly stating their opinion. From the perspective of an individual, opinions from a stranger may not have the same impact or viewed with the same level of trust as an opinion from a friend or relative or even a celebrity. But if several strangers have similar sentiments then the opinion can be considered significant.

TABLE I. Opinion classifications

ID.	Class	Opinion
1.	Positive	Volvo buses from various parts of city to Airport is a good initiative.
2.	Negative	It is hard to find a good souvnir, shops keep very old merchandise.
3.	Neutral	Nothing great about the airport, its functional
4.	Constructive	Small trolley for cabin baggage and shopping would be good.

In the literature, opinions have been classified as *positive, negative* or *neutral* (Table I). In our view there is also a fourth type – a *constructive* opinion. Many times people give suggestions to improve or make the product or service better. Constructive opinions need not imply that the opinion holder is negatively inclined about the entity. Being a classification problem, many supervised machine learning approaches have been applied with different degrees of success. The main problem faced here is the need for an annotated training dataset. In addition, several aspects of opinion mining pose unique challenges. These include cross-domain classification, sarcasm detection and spam identification.

Although opinion mining has elicited enormous interest, research in this area is fragmented and disparate. To our knowledge, there is no overarching picture about the entire landscape. In this paper we address this problem by proposing a faceted classification of the opinion mining problem and place elements from the literature in this schema. We also present a generic workflow that characterizes an opinion mining process and delve into specific challenges.

II. Facets of Opinion Mining

Research in opinion mining can be classified into two broad facets (Figure 1). Research on *Opinion Structure* involves mapping of unstructured, opinionated text to structured knowledge elements. Second, research on *Opinion Mining Tools and Techniques* focus on methods to extract opinion structure and aggregation of sentiments.

A. Opinion Structure

An opinion is an *expression of sentiment* by an *author* about *something* or an *aspect* of something. The three important elements of opinion are (a) a *target entity* about which opinion has been expressed, (b) an *author* who has expressed

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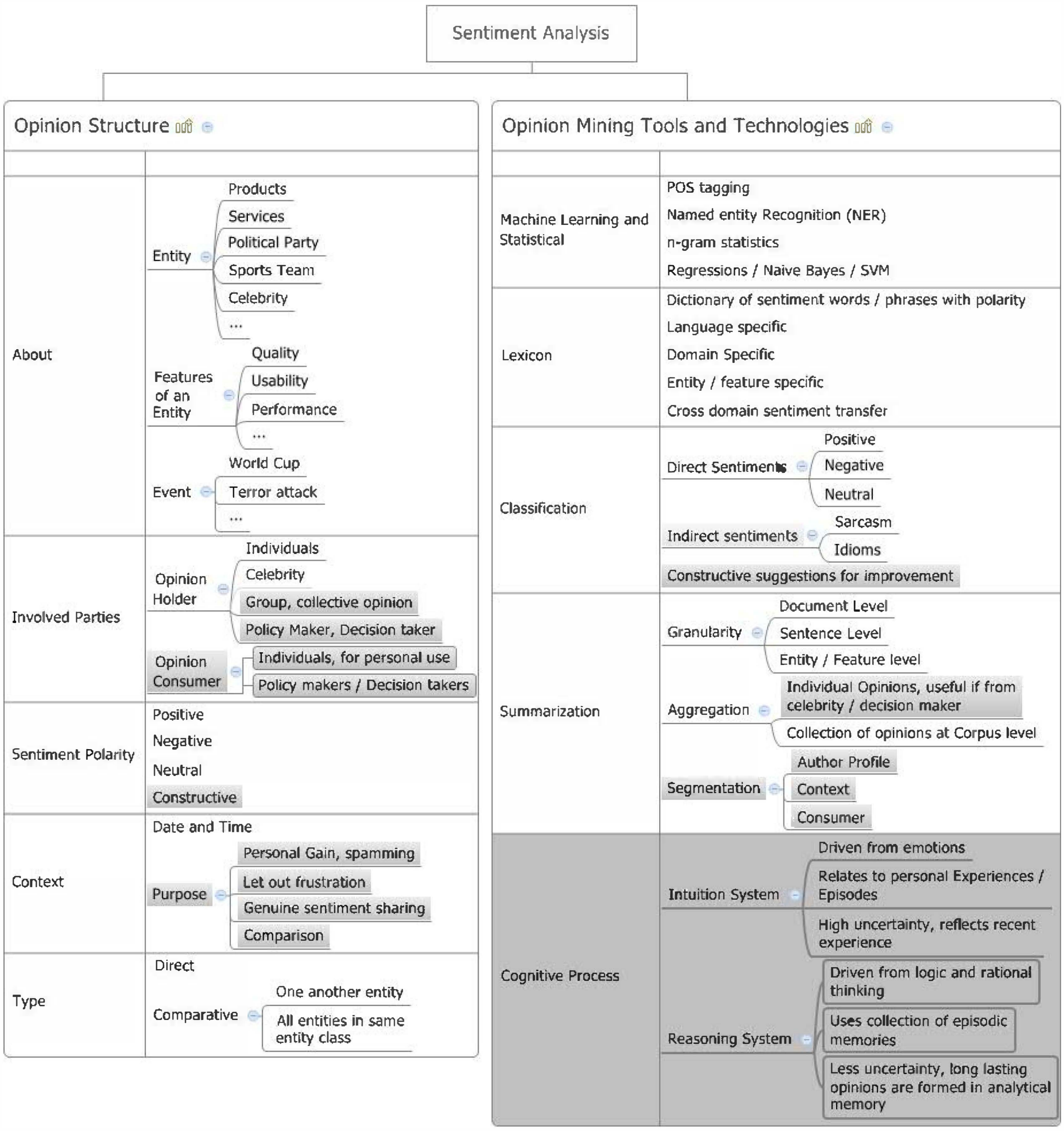

Fig. 1. Two facets of sentiment analysis, grey items indicate areas with none or little research

the opinion, and (c) *sentiment* about the entity held by the author. Liu [13] proposed a quintuple model for opinion structure which includes time of opinion and feature of the entity.

Polarity can be *positive*, *negative* or *neutral*. Entities and features are connected via an entity hierarchy with root node as the entity, while other nodes are the features. In the opinions 1 and 2 in Table II, *Honda Civic* is the entity while *air-conditioner* is an aspect of *Honda Civic*.

In addition to the elements of an opinion expressed above, in our view, there are three other components of an opinion which could provide deep insights, namely: (a) *purpose* of the opinion, (b) *consumer* of the opinion, and (c) the opinion *type*.

The author's *purpose* or *background motivation* for writing the opinion provides deeper insight into the credibility of the sentiments expressed. Businesses may flood social media with positive sentiments about their products and services, resulting in *opinion spamming*. Understanding the background in which the author is writing this opinion would give valuable insights into the credibility of the opinion.

Earlier, there was no mechanism in place to see the *consumers* of an opinion, and understand if they find it useful. Now, several platforms like Facebook, LinkedIn and review sites, allow users to provide a feedback on the content by either selecting *like* or *dislike* icons; or explicitly mention if they found the content to be useful. This provides a window into the opinion consumers. Profiling consumers can help businesses understand the impact of an opinion, and possibly predict network effects like opinion snowballing.

Opinions can also be classified (Table II) into three *types*:

TABLE II. OPINION CATEGORIES

ID.	Type	Opinion
1.	Direct	Air-conditioner of Honda Civic is very efficient
2.	Direct	Ground clearance of Honda Civic is very low which results in touching all the speed breakers
3.	Indirect	What a movie to catch a good sleep!
4.	Comparative	Air-conditioner of Honda Civic is more efficient than Toyota Innova
5.	Comparative	Air-conditioner efficiency of Honda Civic is the best in its class

direct opinions, *comparative opinions* and *indirect opinions*. *Indirect opinions* are either implied as in *idioms* or expressed in a reverse way as in *sarcasm*.

B. Opinion Mining Tools and Technologies

Research focus in this facet, has primarily been to extract one or more elements of the *opinion structure*, and summarize *overall opinion sentiment*.

1) Opinion Structure Discovery: Current state-of-art methods to extract *opinion structure* have used either *rules-based* approach, or *machine learning or statistical algorithms* with a *lexicon*. A lexicon is a language-specific dictionary of words with a predefined polarity. For example, *good, like, happy, excellent* etc. refer to **positive** sentiments while *bad, dislike, disappointed* etc. refer to **negative** sentiments.

There have been a lot of research effort into *lexicon acquisition* [9], [11], [20], [21], [27]. However, the problem is still open with a number of challenges like the following:

1) A lexicon is language specific.
2) Word polarity is domain specific. For example, *quiet* refers to a positive sentiment in a car while it is a negative sentiment for a phone.
3) Polarity is also context specific within a domain. For example, *long* is a positive sentiment for *battery life* of a laptop but it refers to a *negative* sentiment for *startup time* of the laptop.

Domain and context specific nature of the lexicon has resulted in research into *cross domain sentiment transfer* [1], [4], [16], [29]. A lexicon from a source domain and few seed sentiment words from target domain are used to learn a classifier for the target domain. With every new target sentiment word learned, this process is repeated to learn new words and a sentiment classifier for the target domain.

Identification of *entity* and its *aspects* – the other two key components of the opinion structure, heavily relies on statistical methods like Named Entity Recognition (NER) and topic models [3], [12], [20], [26]. Qui et al. [21] proposed a double propagation method using co-occurrences of aspects and sentiments to learn new aspects and sentiments starting with a seed set of aspects and sentiments.

Another challenge in opinion mining is *sarcasm* detection. Sarcasm reverses the sentiment polarity of the literal sentiment expressed in the document. This can lead to wrong conclusions about the sentiment. For example, in the comment, "*The country's economy is in an excellent state, it can only go up*", the author actually meant that economic state of the country is at its lowest point (negative sentiment), but statement uses positive sentiment words like *excellent* to express it. Detection of sarcasm by humans is itself a challenging area. This makes availability of a "gold standard" of manually annotated sarcastic comments, for validation a challenge. Research in sarcasm detection is in its nascent state.

2) Sentiment Aggregation and Summarization: Opinion summarization requires two decisions: (1) the *granularity* at which opinions should be extracted from the corpus and (2) *aggregation level* for overall opinion sentiment. Depending on the application's need, one of the three granularity levels can be chosen for analysis [14]:

Document Level Sentiment Analysis: Here, the assumption is that a document contains an opinion for only one entity and aspect. The summarization task reduces to finding an overall sentiment score at the document level. Both supervised [2], [7], [17], [18], [22] and unsupervised machine learning methods [9], [27] have been used in the literature, to classify a document's sentiment polarity.

Sentence Level Subjectivity and Sentiment Analysis: This is similar to a document level sentiment analysis but done at a sentence level [30]. It assumes each sentence contains an opinion for one entity and aspect, and some of the sentences may not be opinionated (objective). A two stage inference is done for each sentence: first, each sentence is classified as *subjective* or *objective* and then the polarity of each of the subjective sentences are inferred.

Aspect Level Sentiment Analysis: It assumes that a document contains opinion on several entities and their aspects. Aspect level analysis requires discovery of these entities, aspects, and sentiments for each of them.

Using opinion structures at the required granularity, overall sentiment is *aggregated* at the corpus level. Simple and weighted aggregations are used depending on the objectives. Weight could be assigned based on likelihood it is spam or importance of the feature.

Figure 2 summarizes the different facets of opinion mining discussed above and proposes an integrated, generic workflow for an opinion-mining engine.

In the subsequent sections, we shall drill down into each of the facets discussed above to characterize the state-of-the-art and address specific models and challenges.

III. ENTITY DISCOVERY AND ASPECT IDENTIFICATION

Opinions are attached to some entity or event. An opinion mining activity starts with a pre-determined *base entity* in question. Entity discovery task then reduces to identifying all the synonyms of the base entity in the corpus. This problem is characteristic of *Named Entity Recognition (NER)* and *anaphora and co-reference resolution* which has been studied in great detail in NLP.

Aspects could be explicitly mentioned in a sentence or implied (implict). For example, in the sentence: *This laptop is very expensive* – "price" is an *implicit* feature: Lack of language constructs in the sentence makes implicit aspect extraction a complex problem. Most research have focused on extracting only explicitly mentioned aspects.

Explicit aspects are normally nouns and noun phrases in a sentence around the base entity. Methods based on POS

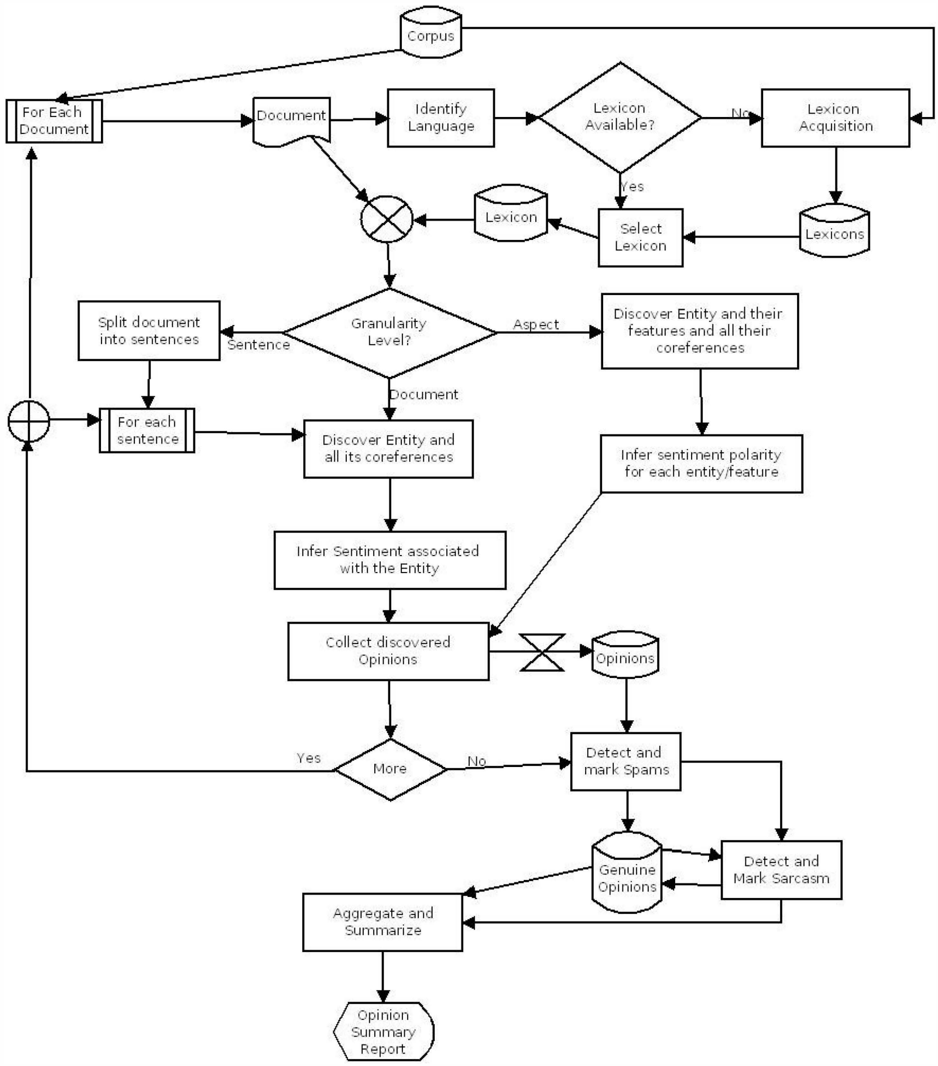

Fig. 2. Integrated Opinion Mining Flow

tagging and topic models have been used to identify them. Some of the widely used methods are discussed below.

Frequently used phrases method is based on the hypothesis that frequently used noun phrases are the key aspects of the entity and people's choice of words normally converge. Infrequent nouns are generally *less important* or not considered important aspects.

Hu and Liu [12] use this approach to extract aspects from customer reviews. They use a POS tagger to tag sentences and then use an Apriori algorithm to extract up to 3-gram frequently used phrases.

Popescu and Etzioni [20] propose a feature assessment method named OPINE, based on *point-wise mutual information* (PMI) statistics for words, proposed by Turney [27] [refer equation 1]), to estimate if a noun or a noun phrase is a potential feature for an entity. They use a product feature (f) and its relationship (d) with entity to calculate PMI score ($hit(f)$ is the number of hits from a search engine for the query: `f`):

$$PMIIR(f,d) = log_2\left(\frac{hit(f \wedge d)}{hit(f)\cdot hit(d)}\right) \tag{1}$$

Qui et al. [21] use co-occurrence of aspects and opinion sentiment words to extract both aspects and opinion words. It is a semi-supervised method which requires few initial seed aspects and opinion words. For example, consider the following opinionated statement about a car: *This car's engine is amazing and its computer has amazing features*. Here, *engine* could be a frequent feature but it is possible that not many people would write about the car *computer*. Given that an opinion term *amazing* co-occurs with *engine* and *computer*, the model can infer that *computer* would also be a feature of the car. This is a single propagation, propagating from opinion word to a feature. Using newly acquired features, the model continues to discover new opinion tokens attached to the new feature. This is the second propagation – from features to opinion tokens. Double propagation method is used iteratively till no new features and opinion words are discovered.

Topic models like LDA [3] have also been used to identify features. Graber et al. [5] extend LDA to use random walk on WordNet synaset (sets of synonyms) as an additional source of word generation. Mei et. al [15] propose a *topic-sentiment mixture* generative model which extracts both topics (as features) and sentiments together.

IV. Lexicon Acquisition

Lexicon acquisition is typically a two step process: (1) identify sentiment defining words and phrases and (2) classify these words with sentiment polarity – *positive, negative* or *neutral*.

A widely used approach for lexicon acquisition is by using a *seed lexicon*. In this approach, a vocabulary of words and phrases is used, each of these words and phrases have *positive*, *negative* or *neutral* sentiment. Acquisition of the lexicon is a two step process. In step one, opinionated words are identified in the document and in step two, polarity of the opinionated word is inferred.

A. Sentiment Word Identification

Opinion words and phrases are normally adjectives which can be extracted using POS tagging tools. Turney [27] used PMIIR score (equation 1) to compute likelihood of a word to be an adjective

In order to identify if a word w is a sentiment word or not, PMIIR score for the phrase is compared with a known positive and negative sentiment words like "*excellent*" and "*poor*" and thresholded against a threshold t - $max(PMIIR(w, \text{"excellent"}), PMIIR(w, \text{"poor"}) > t \Rightarrow Opinion$.

Dictionary based methods use an initial (seed) list of opinion words and searches a dictionary like WordNet to find its synonyms. This is an iterative approach and the iteration stops when no more synonyms are added. Hu and Liu [11] use this approach but found that it required a manual inspection to filter out non opinionated words. Another problem with dictionary based methods is that they cannot be used to build domain-specific lexicon.

Qui et. al [21] use a *double propagation method* to discover features and opinion phrases simultaneously using their co-occurrence in the corpus. This approach requires a large corpus. Since domain specific corpus may be limited in size, this approach can be used to discover generic opinion lexicons.

B. Semantic Orientation

PMIIR score based method not only can be used to classify words as sentiment defining words, but also to provide a measure to classify them into *positive* or *negative* polarity based on the PMIIR score with *excellent* and *poor*.

Another popular method deployed to detect semantic orientation is a semi-supervised learning method and using seed words. Hatzivassiloglou and McKeown [9] use connective words which combine similar or dissimilar meaning sentiments. Similar meaning connectives like *AND* are used to connect either *positive* or *negative* sentiments. It is hard to find opinions like "*Honda Civic is spacious and difficult to drive*" Likewise, disjunctions (BUR, OR, EITHER-OR,..) joins two dissimilar opinions. Some other common rules used are (1) NEGATION words like "*not*" reverses the polarity of the sentiment words, (2) Decrease and increase of opiniated items like "*This pain killer decreased my pain significantly*." Pain is a negative sentiment word and "*decrease of pain*" makes positive sentiment for the medicine.

A graph with adjectives as nodes and two sets of edges – similar, dissimilar orientation is formed. Graph clustering is used to group them into two to three clusters.

Popescu and Etzioni [20] propose an unsupervised approach called *relaxation labeling*, based on the sentiment of the entity's neighborhood. A graph with nodes as entity and edges defined by connectives is created. Each node is assigned a probability for each of the three sentiments (positive, negative and neutral). Initial probabilities are assigned using PMIIR. Probabilities are updated based on the sentiment probabilities of the neighborhood of the entity. It is an iterative process and iterations stop when global level sentiment does not change for few iterations. In the update iterations, an assumption is made that neighborhood node's probabilities are independent of each other. Sentiment polarity is assigned as the sentiment with maximum probability.

V. Sarcasm Detection

Sarcasm and irony are difficult verbal behaviors and many people who attempt to use them, fail to accomplish their task. Sarcasm expresses an opposite *semantic* meaning of what is *literally* written. Even people find it difficult to recognize sarcasm. The ability to comprehend sarcasm requires a complex sequence of cognitive skills by the listener/reader.

Reyes and Rosso [24] used supervised learning approach to learn a set of classifiers – NB, SVM and decision trees to classify irony. All the classifiers had similar performance achieving 75% accuracy. Focus of their study was on two key elements of modeling: (a) training data and (b) feature set. They adopted a novel technique of using *wisdom of crowd* to collect positive labelled data set. Five products were identified which had gone viral and had a large number of reviews posted. All the reviews with ratings lower than four (4) were removed from the set. They hypothesesized that the purpose of viral effect is to increase the popularity of the product by exalting superficial properties of the product, thus a rating given would be high. Negative class of data (non-ironic) was collected for the products having lots of reviews and normal sales (non-viral effect). Other than syntactic and semantic features they used stylistic features like *Funny profiling*, *Affective profiling* and *Pleasantness profiling*.

In another approach, Gonzalez-Ibanez et. al. [8] use twitter to collect a training dataset. They use hashtags to collect sarcastic (*#sarcasm* and *#sarcastic*), positive (*#happy*, *#joy*, *#lucky*) and negative (*#sadness, #angry, #frustrated*) tweets. Classifiers were learned using two sets of features (a) Lexical and (b) Pragmatic are used to represent the tweets.

Lexical features include n-grams and a dictionary. Dictionary based features were derived from (a) LIWC [19] word classes, (b) WordNet-Affect [28], and (c) interjections (eg. ah, oh) and punctuations (eg.!,?). Three pragmatic features were used in the experiments: (a) Postive emoticons like smiley, (b) Negative emoticons like frowning face and (c) Indications that the tweet was in response to another tweet.

Automatic detection of sarcasm is still a challenge and a wide open research area.

VI. Conclusions

Opinion mining is a vast research area with several open problems. In this paper we attempted to characterize this landscape under a schematic framework and also throw light on areas ripe for further research. To the best of our knowledge, there is no similar work on such a characterization of this research area.

Due to space constraints, several elements of the opinion-mining landscape were excluded from this paper.Nevertheless, our hope is that the provided schematic framework would be a valuable tool for researchers to quickly understand this landscape.

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