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2 authors:

Toqir A. Rana
University of Lahore

Yu-N Cheah
Universiti Sains Malaysia

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Aspect extraction in sentiment analysis: comparative analysis and survey

Toqir A. Rana[1] · **Yu-N Cheah**[1]

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Abstract Sentiment analysis (SA) has become one of the most active and progressively popular areas in information retrieval and text mining due to the expansion of the World Wide Web (WWW). SA deals with the computational treatment or the classification of user's sentiments, opinions and emotions hidden within the text. Aspect extraction is the most vital and extensively explored phase of SA to carry out the classification of sentiments in precise manners. During the last decade, enormous number of research has focused on identifying and extracting aspects. Therefore, in this survey, a comprehensive overview has been attempted for different aspect extraction techniques and approaches. These techniques have been categorized in accordance with the adopted approach. Despite being a traditional survey, a comprehensive comparative analysis is conducted among different approaches of aspect extraction, which not only elaborates the performance of any technique but also guides the reader to compare the accuracy with other state-of-the-art and most recent approaches.

Keywords Aspect extraction · Aspect-level sentiment analysis · Explicit aspect · Implicit aspect

1 Introduction

Sentiment analysis (SA), also known as opinion mining (OM), deals with the identification and extraction of user's opinions or emotions, expressed over different blogs, social sites, discussion forums, merchant's/manufacture's websites, etc. With the evolution of WWW, SA has become one of the most vigorous research areas in computer sciences. Specially, people's interaction and curiosity, towards social media and WWW, has attracted many researchers

✉ Toqir A. Rana
toqirr@gmail.com

Yu-N Cheah
yncheah@usm.my

1 School of Computer Sciences, Universiti Sains Malaysia (USM), 11800 Penang, Malaysia

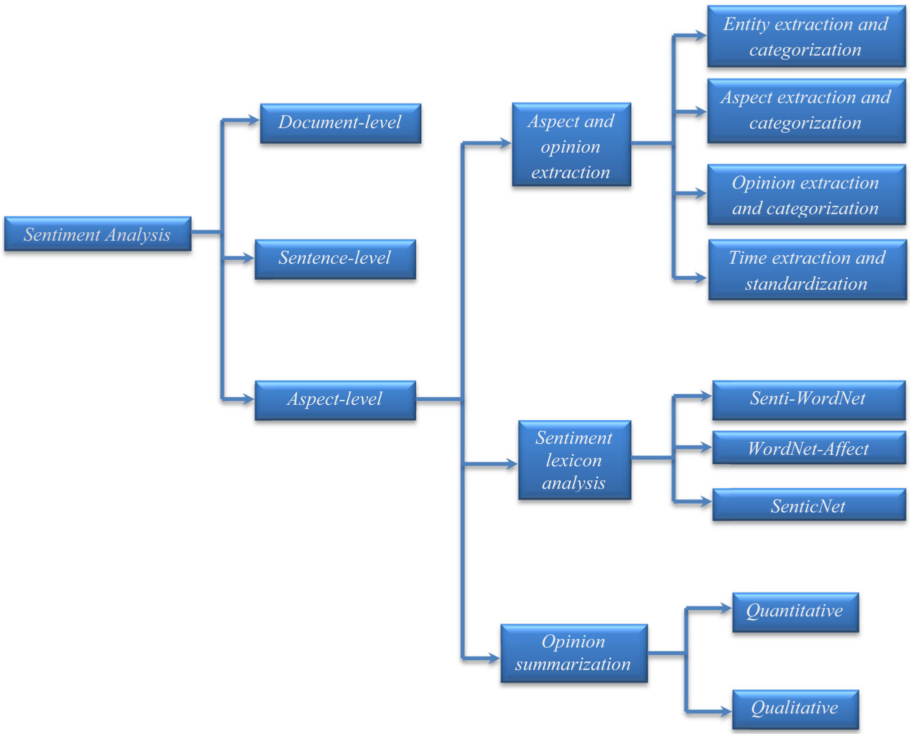

Fig. 1 Classification levels of SA

to explore the user's behavior towards a specific topic. This helps managers, officials, policy makers and decision makers to judge the impact of their product, service, or policy over the community. Therefore, the task of SA should be carried out in deliberative fashion, as it can convey the ambiguous or erroneous information and mislead the higher management to conceive the precise decision.

There are different classification levels of SA: (1) document-level, (2) sentence-level, and (3) aspect-level (Liu 2012). The basic task of document-level sentiment classification is to deal with the extraction of opinion baring words from reviews, and detecting the polarity of these opinionated terms (Pang et al. 2002; Turney 2002). On the basis of these opinionated terms, the system decides whether the review expressed overall positive opinion or negative about the topic. Sentence-level sentiment classification deals with the identification of a sentence as subjective or objective and hence, also called as subjectivity classification (Wiebe et al. 1999). These subjective sentences are considered as small documents and further classified by extracting and classifying opinions as positive or negative. Aspect/feature-level SA is a more fine-grained model, which extracts opinions expressed against different aspects/features of the entity (Hu and Liu 2004a). This involves extraction of aspects and opinions, and categorizing them into similar classes, determining the polarity of opinions and summarization of results. Figure 1 shows the different classification levels and the subtasks of aspect-level SA (Liu 2012; Liu and Zhang 2012).

From the last decade, a huge number of research articles have been presented on different granularity levels of SA. Pang and Lee (2008) and Liu (2012) discussed the fundamental knowledge on the problem of SA and presented a comprehensive survey for different approaches. Liu (2010) has presented hypothetical explanation for different concepts and approaches in SA and subjectivity. Liu and Zhang (2012) conducted a meticulous survey and Zhang and Liu (2014) provides the details for the extraction of aspects and entities from reviews. Taytsarau and Palpanas (Tsytsarau and Palpanas 2012) not only presented a detailed survey, but also notified some limitations in existing approaches and discussed new research directions.

Despite of above mentioned exhaustive surveys, Feldman (2013), Cambria et al. (2013) and Montoyo et al. (2012) have prearranged short surveys on SA. Medhat et al. (2014) and Orimaye et al. (2015) focused on document-level and sentence-level SA and presented meticulous and comparative analysis of different approaches. Therefore, in this survey, we have focused on aspect-level SA and especially on aspect and opinion extraction phase.

Aspect-based SA task can be divided into three main subtasks i.e. (1) aspect and opinion extraction, (2) sentiment lexicon analysis and (3) opinion summarization (Hu and Liu 2004a). Sentiment lexicon analysis is to find the polarity of opinion words which were extracted during task 1 i.e. the aspect has positive opinion or negative. The most used publically available lexicons for this task are: Senti-WordNet (Esuli and Sebastiani 2006), SenticNet (Cambria et al. 2010) and WordNet-Affect (Strapparava et al. 2004). Opinion summarization is the presentation of extracted aspects and the polarity of their opinion words in qualitative (Liu et al. 2005) or quantitative (Hu and Liu 2004a) fashion. The aspect and opinion extraction task is the most important and challenging task among them all and hence, studied by most of the researchers as compared to the other tasks. This task is further divided into multiple subtasks as illustrated in Fig. 1. Liu (2012) has specified a detailed explanation on each of the subtask.

Let us take an example to understand different chores of aspect-based SA. Consider the review[1]: “I bought an iPhone a few days ago. It was a nice phone. The touch screen was really cool”. In this review, *iPhone* is the entity and *touch screen* is an aspect of this entity. *Nice* and *really cool* are the opinion words which target the entity and aspect respectively. Aspect and opinion extraction phase includes the extraction of entity, aspect and opinion words mentioned in the above review. While, sentiment lexicon phase deals with the opinions and analyze whether the opinion words extracted have the positive polarity or negative. In the end, opinion summarizing is to present all the aspects and the polarity of opinion words in an effective way.

In this paper, we have surveyed different techniques for the extraction of aspects from online reviews. Extracting the aspects from free text is a challenging task in SA. Hu and Liu (2004b) have identified two different kinds of aspects i.e. explicit and implicit. Explicit aspects are those aspects which used by users with explicit words e.g. in the review: “It’s light weight enough to take with you everywhere, but powerful enough to get outstanding pix”, the aspect *weight* has been expressed explicitly. On the other hand, in review: “It is light enough to carry all day without bother”, user is again talking about the *weight* aspects but this time no explicit word has been used to express this aspects. The extraction of explicit aspects is widely studied by the researchers and several diverse approaches have been anticipated. However, very little work has focused on the identification of implicit aspects due the complexity of tracing them from reviews. Therefore, on one side we have presented the comparison and analysis of verity of techniques for explicit aspect extraction, but on the other hand we have discussed different approaches proposed for the identification of implicit aspects.

[1] www.amazon.com

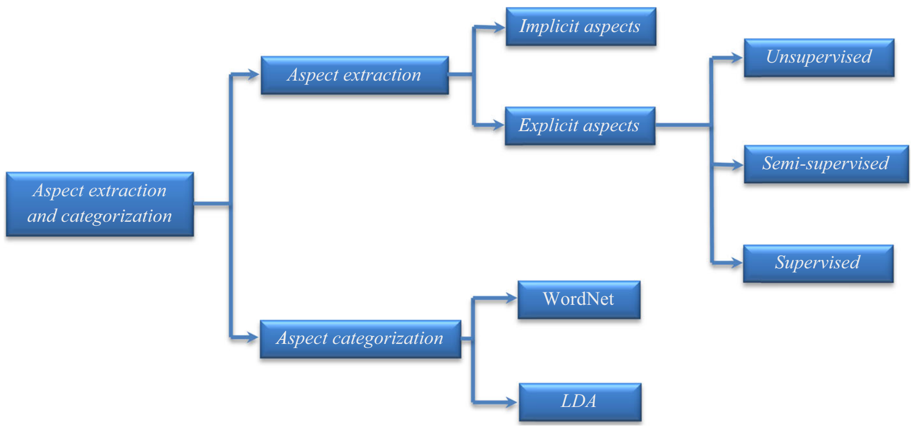

Fig. 2 Aspect extraction approaches

2 Methodology

As reported by Feldman (2013), more than 7000 articles have been written on different areas of SA. Therefore, we have included the most recent or state-of-the-art papers in this survey. Although, we have not included topic modeling techniques (e.g. Latent Dirichlet Allocation (LDA)) for aspect extraction in this study, because the comparison of topic modeling approaches with the techniques presented in this review is not conceivable, due to the unavailability of precise results. More than 50 techniques were summarized for the extraction of explicit aspects. But for implicit aspects, we have found only 11 studies which focused on the extraction of implicit aspects, while some studies focused on both implicit and explicit aspects. Due to the large number of research papers for explicit aspects, we have divided the approaches into three main categories i.e. unsupervised, semi-supervised and supervised, as illustrated in Fig. 2.

The task of aspect extraction and categorization has two parts, first to extract all aspects and second to classify similar aspects into clusters. The aspects are categorized into two types i.e. explicit and implicit and further explicit aspects are classified according to the nature of the adopted approach. For aspect categorization part, most of the researchers proposed dictionary [WorNet (Miller and Fellbaum 1998)] or corpus-based approaches. Despite of dictionary-based approaches, some researchers have used LDA (Blei et al. 2003) to group similar aspects. In this paper, we have focused only aspect extraction phase and hence, aspect categorization is not discussed.

In the next sections, we will briefly explain different techniques used for the explicit and implicit aspects. Then the contribution of this survey, a comparison has been conducted among different aspect extraction techniques, elaborated the effectiveness in different domains and languages.

3 Explicit aspect extraction

Extraction of explicit aspects from online reviews is the key task in aspect-based SA. For the sake of convenience, we have classified the techniques of explicit aspect extraction into three major classes i.e. unsupervised, semi-supervised and supervised. The summary, of all three classes, has been elaborated in the form of a table in each section. In Tables 1, 2 and 3, we have assigned the model names where authors did not used any and highlighted with a "*".

3.1 Unsupervised

Unsupervised techniques have been widely used by the researchers for the extraction of aspects from online reviews. These techniques have been applied on diverse kind of domains and of different language datasets. Most of the approaches have focused customer reviews dataset which was first used by Hu and Liu (2004b). These datasets were prepared for the product reviews domain but other domains were also explored as elaborated in Table 1.

Table 1 Summary of unsupervised techniques

References	Year	Model	Algorithm used	Domain	Language	Implicit aspect
Hu and Liu (2004a)	2004	FBS	Frequency-based	Product	English	No
Popescu and Etzioni (2007)	2007	OPINE	PMI	Product	English	No
Li et al. (2009)	2009	NLPS*	NLP + statistical	Mobile	Chinese	No
Raju et al. (2009)	2009	FB1*	Frequency-based	Product	English	No
Moghaddam and Ester (2010)	2010	Opinion Digger	Frequency-based	Product	English	No
Meng and Wang (2009)	2009	FB2*	Frequency-based	Product	Chinese	Yes
Zhu et al. (2011)	2011	MAS	Bootstrapping	Restaurant	Chinese	No
Eirinaki et al. (2012)	2012	HAC	Frequency-based	Product	English	No
Liu et al. (2012)	2012	WTM	Word alignment + Graph-based	Product	English	No
				Restaurant	Chinese	
				Hotel	English	
				MP3	English	
				Product	Chinese	
Bafna and Toshniwal (2013)	2013	FPB*	Frequency + Probability-based	Product	English	No
Marrese-Taylor et al. (2013a, 2014, 2013b)	2013, 2014	OZ	Frequency-based	Tourism	English	No
Bagheri et al. (2013a, b)	2013	BST1*	Bootstrapping	Product	English	Yes
Htay and Lynn (2013)	2013	PT-Based*	Pattern-based	Product	English	No
Bancken et al. (2014)	2014	ASPECTATOR	Syntactic dependency	Movie	English	No
				MP3	English	
Du et al. (2014)	2014	TrLM	Word alignment-based	Product	English	No
Poria et al. (2014)	2014	Rule-based*	Rule-based	Product	English	Yes
Li et al. (2014, 2015)	2014, 2015	SSPA	Bootstrapping	Product	English	No

Table 1 continued

References	Year	Model	Algorithm used	Domain	Language	Implicit aspect
Hai et al. (2014)	2014	IEDR	Rule-based	Product Hotel	Chinese	No
Quan and Ren (2014)	2014	PMI-TFIDF	PMI	Product	English	No

3.1.1 Frequency or statistical

The problem of aspect-based SA was first studied by Hu and Liu (2004b). The idea was to extract all frequent aspects from customer reviews and then find the opinion words associated with them. Frequent aspects were those aspects about which most of the users like to express their views. For this purpose, Apriori (Agraval and Srikant 1994) based association rule miner CBA (Liu et al. 1998) was applied. It was observed that, usually nouns/noun phrases represent any aspect in a sentence. Therefore, all the nouns/noun phrases were extracted from the documents and such nouns/noun phrases were labeled as frequent aspects which have the support higher than the given threshold. Once all the frequent aspects were selected, then the nearest adjectives were extracted as potential opinion words. By this, they have extracted aspect opinion pairs and called these aspects as frequent aspects. Hu and Liu have also reported that not all the aspects are frequent. If a sentence has some opinion word but does not has any frequent aspect, then the nearest noun to that opinion word was extracted as infrequent aspect. This generates lists of frequent and infrequent aspects along with their opinion words.

Hu and Liu (2004a) proposed extension in their previous work (Hu and Liu 2004b) by adding two more steps along with aspect and opinion extraction. First step is to find the polarity of the opinion words and the second step to summarize the results and representing reviews as positive or negative. The first step involves finding orientation of opinion words and ranking them as positive, negative or neutral. Senti-WordNet was employed to identify sentiment orientation of opinion words. The final step was to generate a summarized detail of the reviews. They put sentences into positive and negative categories and presented a summary that how many users have expressed their positive reviews and how have expressed their negative reviews and giving an overall picture of the review on different aspects.

Hu and Liu's approach was further improved by Bafna and Toshniwal (2013) integrating probabilistic approach. The extraction of aspects was carried out by association rule mining. All the frequent nouns, as nouns represent aspects in most of the cases, were extracted. But not all the nouns represent as potential aspects, so they have used probabilistic power equation to remove all such nouns which do not represent aspects although they are frequent. As all the aspect words extracted and grouped together, the next step was to extract opinion words and for this the nearest adjective was extracted as potential opinion word for any extracted aspect.

Li et al. (2009) combines NLP with statistical methods to identify aspects from mobile phone domain in Chinese language reviews using dictionary of aspects and opinion words. Raju et al. (2009) proposed a three step approach i.e. pre-processing, clustering and attribute extraction to extract aspects from reviews. First they extract all nouns/noun phrases and then classify them into clusters. Then these clusters were used to identify aspects. Their approach was domain independent.

Reviewing websites provide some additional information along with customer reviews which are a set of defined aspects and a rating guideline from 1-5 stars. Using this existing information, an unsupervised approach was proposed to extract aspects from customer reviews (Moghaddam and Ester 2010). In this approach, authors used known aspects from reviews to extract explicit aspects from free texted customer reviews. Also, they generated aspect raking from 1-5 on the basis of rating guidelines provided by the review websites. Meng and Wang (2009) also used additional information of products available on review websites. Also, they defined associations among aspects and opinions to identify implicit aspects.

An opinion mining search engine AskUs was presented by Eirinaki et al. (2012). They introduced two algorithms, first for extracting aspects and opinions from the document and second to rank the extracted aspects. The system proposed was not only to find the polarity of opinions against any aspect but also gives the aspect ranking on the basis of the number of opinion words representing that aspect. To extract potential aspects the algorithm High Adjective Count (HAC) was proposed. This algorithm finds all nouns in the document as potential aspects and adjectives as potential opinion words and also assigns a score to each noun. If same noun has more adjacent adjectives in different sentences, then it means that same aspect has been ranked by more than one opinion words. This score can further be used to select those nouns as aspects that have score higher than given threshold. The second algorithm ranks the extracted aspects on the basis of their score calculated by first algorithm.

Marrese-Taylor et al. (2013b) proposed an extension to aspect-based opinion mining techniques to use it for tourism domain i.e. hotels and restaurants. They define a sentence as ordered set of tokens and tokens could be words or punctuations. Also if any token come twice in a sentence, it will be considered as two separate tokens at distinct positions. By this definition they calculated the distance between two words and used this for the extraction of aspects. Further they have followed rule-based techniques (Ding et al. 2008) for the determination of the opinion orientation. This technique was further adopted to propose OpinionZoom (Marrese-Taylor et al. 2013a), modular software to evaluating the opinions from tourism domain. Moreover, Marrese-Taylor et al. (2014) extended the same work for the development of a generic architecture which they used to create a prototype analyzed the opinions of tourism domain from tripadvisor.com. Their methods showed a poor precision for explicit aspect extraction i.e. 35 % but F-measure was at 92 % for sentiment orientation.

3.1.2 Bootstrapping (Unsupervised)

Zhu et al. (2011) presented a multi-aspect bootstrapping (MAB) method to identify aspects from Chinese language restaurant reviews. The purpose of this algorithm is to extract all those aspects from a sentence, against which user has expressed his views. User can express its views against more than one aspect; therefore, MAB was proposed to extract all aspects from a sentence without using any labeled data. Once all the aspects were available, the next task is to find all the opinion words which represent the sentiment of user over any particular aspect. For this purpose they proposed Multi-aspect segmentation (MAS) which also takes such sentences as input, which have more than one aspects and produce segments with multiple aspects and using these segments they identify the opinion words.

Bagheri et al. (2013b) used bootstrapping algorithm approach, which needs initial seed sets of aspects. To identify aspects from the reviews, they defined several POS patterns based on heuristics. They define a new matric A-score which uses inter-relation information among words, and with this a list of top aspects was generated. This information of aspects was used through bootstrapping algorithm to generate the final list of aspects by using the A-score of each aspect to measure the value score. As the final list of aspects generated, the next step was to eliminate all those aspects which were redundant. For pruning phase, two methods were introduced subset-support pruning and superset-support pruning. These both methods finally generates final list of aspects without having redundancy. Same approach was used to identify implicit aspect by adding graph-based approach (Bagheri et al. 2013a). The opinions words were used in the graph as node and this node mapped to a set of aspect nodes. The weight was allocated to the edges i.e. aspect and opinions to identify the co-occurrences. Further a function was defined to measure the association among aspects and opinion words. This association will increase the weight of the edges and on the basis of graph threshold, which was defined to identify the gap among different nodes; a list of potential implicit aspects was extracted.

Li et al. (2014, 2015) proposed bootstrapping dependency pattern-based approach to extract aspects and opinions. The rules were defined on the basis of grammatical structure of sentences which define the existing of certain patterns among aspect and opinion words. After extracting aspects, they used semantic similarities based technique to group similar aspects using WordNet. Also they calculated the global reputation of each aspect to find the importance of them i.e. how often users are commenting on those aspects.

3.1.3 Heuristic- or Rule-based

Liu et al. (2012) proposed a Word-Based Translation Model (WTM) to find the association between aspects and opinions. They formulate the task of finding association among aspects and opinions as word alignment task and for this they use monolingual word alignment model. They considered noun/noun phrases as potential aspects and adjectives as their opinions but did not consider the nearest adjective as opinion words and proposed a graph-based model to identify such relations and then select the aspects and opinions which have the confidence higher than the given threshold. Htay and Lynn (2013) define certain patterns to identify the correlation among aspect and opinion words.

To automatically detect and rate the product aspects from customer reviews Bancken et al. (2014) introduced a new algorithm called ASPECTATOR. This algorithm works by matching syntactic dependency path among different words from the sentence. To identify product aspects and their opinion words, ten handcraft dependency paths were defined. First the algorithm generates a syntactic dependency tree by using dependency parser and extracts the basic aspect opinion pair from the sentence. As the aspect and opinion words identified, the neighboring words were searched to identify the complete aspect opinion set. During the extraction of opinion words, the negations were also noticed and such word along with opinion words extracted which negates the whole term. Further to cluster the synonyms WordNet was used and to find the polarity of the opinions Senti-Wordnet was used.

By investigating the complexity of review sentence a Translation-Based Language Model (TrLM), to identify the product aspects, was proposed Du et al. (2014). They studied that the quality of reviews also effect on aspect and opinions words. The framework was divided into three subtasks. First task to predict the importance of each review sentence for which they used support vector machine (SVM) regression model. In the second part, the information gathered in first step was incorporated into monolingual word alignment model, which extracts the modification relations among aspect and opinion words. In the last step the aspect confidence was estimated on the basis of given threshold and only those aspects were selected which has confidence higher than the given threshold.

Poria et al. (2014) proposed a rule-based approach to extract both explicit and implicit aspect from customer reviews. Explicit aspects are concepts which denote the targets in a review sentence and can be extracted by identifying the word representing that concept. But on the other hand, user can express an aspect in indirect manner through an implicit aspect clue (IAC). In the proposed approach, these IAC's were used to identify the implicit aspects and divided the task into two subtasks i.e. identifying the IACs in review sentence and then map these IACs to aspect which they actually representing. To identify such aspects, they defined several dependency rules and used WordNet and SenticNet to identify the synonyms and semantics of each IAC respectively.

Extracting aspects from cross domain relevance was studied by Hai et al. (2014). They adopted rule-based approach to identify aspects and opinion from Chinese language reviews. Once the aspect and opinion pairs are extracted, the Intrinsic-domain relevance (IDR) and Extrinsic-domain relevance (EDR) scores for each candidate aspect were calculated which represent the relevance of an aspect to certain domain. If the IDR value of aspect is greater than given threshold and the EDR value is lesser then that aspect is confirmed as opinion aspect.

3.1.4 Pointwise mutual information (PMI)

Aspect extraction phase, proposed by Hu and Liu, was further modified by increasing the precision (Popescu and Etzioni 2007). They tried to modify the previous technique of aspect opinion extraction by removing those nouns which were not potential aspects. They evaluated each aspect by computing Pointwise mutual information (PMI). If the PMI calculated is too low then it may not be the aspect. They have improved the precision of previous technique by using PMI methods.

To find the association between aspects and domain words, PMI along with Term Frequency-Inverse Document Frequency (TF-IDF) has been used (Quan and Ren 2014). The idea was that, aspect words are closely associated to their domain aspects. For example, entity aspect "photo quality" is closer to "camera" domain as compared to "mp3" domain. For this different domain corpuses are selected and the association between aspects and different domains was calculated by proposed PMI-TFIDF technique. The aspects were then extracted on the basis of dependency distance which calculates the dependency between aspect and its potential opinion word. In the next step those opinion words were filtered which have the lower value of PMI-TFIDF than the defined threshold. The unfiltered opinion words were added to the set of opinion words.

3.2 Semi-supervised

The semi-supervised approaches have been also studied by the researchers. These techniques are partially dependent upon user input and need initial seeds to start the algorithm. Just like unsupervised techniques, these approaches are also commonly focused upon product reviews as shown in Table 2.

3.2.1 Bootstrapping (Semi-supervised)

Wang and Wang (2008) have used context-dependency property to learn product aspects and opinions simultaneously. To identify product aspects and opinions, they used bootstrapping method which takes lexicon of seeded opinion words as input to extract product aspects. Further, they used the mutual information to identify association among aspects and opinion words. To identify infrequent aspects, a linguistic rule was utilized. They used opinion words to identify implicit aspects and by mapping them to explicit aspects. Following similar

Table 2 Summary of semi-supervised techniques

References	Year	Model	Algorithm used	Domain	Language	Implicit aspect
Wang and Wang (2008)	2008	BST2*	Bootstrapping	Product	Chinese	Yes
Hai et al. (2012)	2012	LRTBOOT	Bootstrapping	Cell phone Restaurant	Chinese	No
Hai et al. (2012)	2012	LSABOOT	Bootstrapping	Cell phone Restaurant	Chinese	No
Zhao et al. (2014)	2014	BST3*	Bootstrapping	Product	Chinese	No
Wu et al. (2009)	2009	D-Parser1*	Dependency Parser	Product	English	No
Wei et al. (2010)	2010	SPE	Semantic-based	Product	English	No
Yu et al. (2011a)	2011	D-parser2*	Dependency Parser	Product	English	No
Qiu et al. (2011)	2011	DP	Double Propagation	Product	English	Yes
Zhang et al. (2010)	2010	DP1*	Double Propagation	Product	English	Yes
Ma et al. (2013)	2013	Lexicon-LDA*	LDA + lexicon	Product	Chinese	No
Liu et al. (2013b)	2013	WAM	Word alignment	Product	English	No
Liu et al. (2015)	2014	PSWAM	Word Alignment	Product	English	No
Xu et al. (2013a)	2013	GP-based*	Graph-based	Product	English	No
Samha et al. (2014)	2014	Lexicon-FT*	Frequent tags + lexicon	Product	English	No
Yan et al. (2015)	2015	EXPRS	Page rank + Lexicon-based	Product	Chinese	Yes

approach, Hai et al. (2012) proposed likelihood ratio set (LRTBOOT) and latent semantic analysis (LSABOOT) bootstrapping methods. Zhao et al. (2014) combines a refinement process with bootstrapping method which employs automatic rule refinement to prune out false results and updates the rules to improve aspect and opinion extraction process.

In product reviews, any opinion will always have a target. This property was used to extract opinions and aspects in the research of Qiu et al. (2011, 2009). Initially it was assumed that opinions are usually adjectives and nouns are potential aspects. It was noticed that between aspects and opinion words there always exists a relationship. With the help of these relationships it is possible to extract aspects from known opinions and also opinions from known aspects. Therefor the technique, called double propagation, was introduces to extract opinion and aspects as it not only extracts aspects with the help of opinion words but also extracts opinions with the help of aspects. Initially some seed words were given as input to identify some opinions but not for the aspects. Hence this approach is semi-supervised. Once some opinion words were extracted, using these opinion words target aspects was extracted. Again these extracted opinions and aspects were used to find new aspects or opinions. The process continuous until no new opinion or aspect is found. That's why this approach is called double propagation.

Zhang et al. (2010) improves this method by adding additional rules. They introduced "part-whole" and "no" patterns to identify aspects. In any review, an aspect could be the part of the object class. For example, in "the engine of the car" review, the engine is the part of the car. This was identified by part-whole pattern. They also studied that users express their views in phrases rather than in complete sentence like "no noise". To handle these kinds of aspects “no” pattern was used. Also they studied the importance of different aspects in the same product and ranked the aspects with the help of aspect relevance and aspect frequency.

3.2.2 Dependency parser

A concept of Phrase Dependency Parsing was introduced by Wu et al. (2009) to extract relations between product aspects and opinion words. This dependency parser generates a tree provides connection between different words in the sentence and these connections can represent relations between different phrases in the sentence. The second step was to extract aspects and opinion words from the reviews. They used product reviews as their corpus. They analyzed that in any review set, 98% of product aspects are either noun phrases or verb phrases. Therefore they extracted all the noun phrases and verb phrases as potential aspects and leave all the other phrases as these could cause in decline of precision. Also those aspects were pruned out which have the low threshold and could not be the potential aspects. For the extraction of opinion words, they used the dictionary-based approach and extracted those words which could represent the sentiments. The next task was to find the relations between aspects and opinions. The dependency parser was used to find these relations. They assumed that usually opinion words supposed to appear near to the aspect words. They define a new tree kernel and incorporate it with SVM to find the relations between aspects and opinions. They found the lowest common parent from all possible sub-trees by defining the maximum distance between aspect and opinion word and in one tree it should not be more than 5. This sub-tree will represent the relation between aspect and opinion word in any particular sentence.

Yu et al. (2011a) also followed the phrase dependency parser (Wu et al. 2009) to extract the aspects from reviews. They used list of aspects generated from pros and cons to identify those aspects which were ranked by most of the users. Their work was to rank different aspects by taking in account the aspect frequency and user’s opinions on that particular aspect. To rank such aspects a probabilistic regression algorithm was designed to assign weights to those aspects which were frequently used by the users and sum of weights of opinion word which was used against different aspects of that product.

3.2.3 Lexicon-based

To identify the aspects in a sentence which have subjective opinions, Wei et al. (2010) proposed semantic-based product aspect extraction (SPE) technique. The basic idea to extract aspects from reviews was same as proposed by Hu and Liu (2004a, b). As all the aspects extracted, they provide a list of positive and negative adjectives to identify the opinion word’s subjectivity. On the basis of this list, the sentiment-based refinement step identifies those aspects which were not actually aspects and pruned such aspects out. This was done by identifying opinion irrelevant product aspects on the basis of input list of adjectives/opinions. Also, the semantic-based refinement step identifies the infrequent aspects and adds these aspects in the list of extracted product aspects.

Ma et al. (2013) combines LDA with a lexicon, containing synonyms, to extract aspects from Chinese reviews. They also considered noun/noun phrases as aspects and with incorporating LDA generated a candidate aspect list. This list was further expanded with the help of synonym lexicon. The extended aspect list contains a number of terms which were not actually aspects. Therefore, to eliminate such terms, filtering rules were applied and the aspect list was refined. Yan et al. (2015) proposed a PageRank algorithm to find the association among aspects and sentiment words. They also used the synonym lexicon to expand the aspect list and used the same lexicon, along with the association among explicit aspect and opinion word, to identify the implicit aspects.

Samha et al. (2014) used aspect information provided by the manufacturer to build a manual list of aspects. This list of aspects was used to identify similar aspects from reviews with the help of WordNet. To identify opinion words, opinion lexicon was used which searched for the most common used opinion terms.

3.2.4 Word alignment- or graph-based

Liu et al. (2013a) proposed a Partially-Supervised Word Alignment Model (PSWAM) to find the association among opinions and their target aspects. This idea uses syntactic patterns along with word alignment model to find the relation among words and extract opinions and aspects from the reviews. They adopt the same approach to align the words as used in Liu et al. (2012). They assumed noun/noun phrases as target aspects of opinion words. The purpose of word alignment was to align opinion words with their potential aspects in a sentence. To improve the word alignment and removing expected errors, they use a trained dataset and incorporate it with the alignment process. From these word alignments, they used syntactic patterns to identify the relations among different words which are opinion and aspect words. This generates a number of patterns; therefore, they selected only those patterns which have the confidence higher than the given threshold. To do so, they adopted a graph-based approach and identify all such patterns and with the help of these patterns they extracted the opinion words and their target aspects.

Liu et al. (2013b, 2015) studied the impact of WAM and PSWAM both small dataset and large dataset. Their assumption was that in some cases if the method tested on the small datasets it does not perform well on the large datasets. Therefore, their experimental results show that PSWAM outperforms WAM when both the methods were tested on different datasets which include both small and large category.

Xu et al. (2013b) proposed a two stage approach, Walk and Learn, to extract opinion and aspect words. In the first stage, a Sentiment Graph Walking Algorithm was proposed to find the patterns among opinion and aspect words keeping confidence of patterns in consideration. In the second stage, the extracted aspects were refined by semi-supervised approach TSVM as there could be many nouns which actually do not represent any potential aspect. With the help of this refined aspect list they refined the opinion words list. Further, Xu et al. (2013a) extended the proposed method and give the detailed and in depth view of both the steps.

3.3 Supervised

As compared to unsupervised and semi-supervised techniques, supervised techniques have been applied to a diverse number of domains. Also most of the approaches are applied on English language reviews as shown in the Table 3.

3.3.1 Dictionary-based

For the extraction of Aspect-Evaluation and Aspect-of Relation from blogs, Kobayashi et al. (2007) proposed a technique which not only extracts opinion aspects but also tends to find the association among opinion, aspect and class of the product. The opinion extraction phase was carried out by supervised technique in which a dictionary-based approach was adopted. From these identified opinion words, the aspects were identified with the help of syntactic patterns.

Table 3 Summary of supervised techniques

References	Year	Model	Algorithm used	Domain	Language	Implicit aspect
Kobayashi et al. (2007)	2007	DT-based*	Dictionary-based	Restaurant Cellular phone Automobile	Japanese	No
Jin and Ho (2009) Jin et al. (2009)	2009	Opinion Miner	Lexicalized HMM	Camera	English	No
Jiang et al. (2010)	2010	GFST	Kernel tree	Product	English	No
Li et al. (2010)	2010	ST-CRF*	Skip Tree CRF	Movie Product	English	No
Chen et al. (2012)	2012	CRF1*	CRF	Product	English	No
Jakob and Gurevych 2010)	2010	CRF2*	CRF	Movie Web-service Cars Camera	English	No
Choi and Cardie (2010)	2010	CRF3*	CRF	Question answering	English	No
Huang et al. (2012)	2012	CRF4*	CRF	Camera	English	No
Li et al. (2012)	2012	OTE	Shallow semantic parsing	Web-service University	English	No
Yang and Cardie (2013)	2013	CRF5*	CRF	Question answering	English	No
Cruz et al. (2013)	2013	Tax-based*	Taxonomy-based	Headphone Hotel Cars	English	No

As the opinion aspect pairs were identified, the relations among words and co-occurrence between aspect and evaluation were tested and verified by a corpus-based trained classifier.

A taxonomy-based approach was proposed by Cruz et al. (2013) for aspect-based SA. They have generated taxonomy for the aspects to be extracted. This approach is domain oriented i.e. same word can represent different meanings not only in different domains but also in same document. They selected aspects and annotated opinions, from serene corpus (headphone, cars and hotels), manually with some computer assistance. From these aspects, they built aspect taxonomy which was generated manually by keeping domain in consideration as the product class itself is included in the taxonomy. By the help of aspect taxonomy, the annotated opinions were validated by assuming that the opinion word is appearing somewhere near to aspect word in the sentence. The validation of opinion words is again manual with some help of automated system. If the opinion words are verified then they extracted as potential opinion words and if annotation of opinion is not verified then another opinion word will be chosen and verified and the process continues till all the words in the sentence verified. After this they extended aspect taxonomy and corpus of annotated opinions. Also, they defined cues for the implicit aspects by estimating the probability of opinion words being used i.e. usually about which aspects these opinions are used. By the help of aspect taxonomy and annotated opinions, dependency patterns were generated for finding the correlation between aspect and opinion words.

3.3.2 Lexicalized HMM-based

For the extraction of aspects and opinions from the customer reviews, a lexicalized HMM-based model was proposed Jin and Ho (2009) and Jin et al. (2009). This work not only identifies the product aspects and their opinions but also identified the sentences which contain aspect opinion pair and categorized the opinion words as negative or positive. They first describe the two tag sets, first is the basic tag set which defines different categories of entities and the second tag set defines the patterns for different entities i.e. what is the position of a word in the entity phrase. With the help of these tag sets they manually tagged each sentence representing the patterns between aspects and opinion words. Further, this trained corpus was integrated with the actual tagged data into HMMs. Now, the task was to find the appropriate sequence of hybrid tags (manual tags and actual tagged data) that maximizes the conditional probability. This was done with the help of HMM along with maximum likelihood estimation (LSE). In the next step, they identified the sentences which contain aspect opinion pairs. They eliminated all the sentences which did not contain any opinion word or express some other product. In the last step, they find the polarity of the opinion words considering negation words, as any negation word reverse the polarity of any opinion word.

3.3.3 Tree-based

Jiang et al. (2010) used tree-based approach, Generalized Aspect-Sentiment Tree (GFST), to extract aspects from customer reviews. They defined four different tree kernel spaces to identify aspects from the reviews. The kernel-based methods evaluate the similarity among two trees instead of extracting each individual aspect from each tree. To find the association among aspects and opinions, they used PMI.

3.3.4 Conditional random field (CRF)

Li et al. (2010) proposed Skip-chain CRFs and Tree CRFs for the extraction of aspects and opinions which are based on machine learning framework, Conditional Random Fields (CRF). First they used linear-chain CRFs to identifying the sequential dependencies among continuous words. They learnt that if two words or phrases are connected by conjunction “and”, then both the words have the same polarity and if they are connected by “but”, then both have the opposite polarity. Therefore, to overcome long distance dependency they used Skip-chain CRFs to find aspects and opinions. Also, they proposed to use Tree CRFs to learn the synthetic structure of the sentences in the reviews. Skip-chain CRFs provide the semantic relations with respect to conjunctions and Tree CRFs provide dependency relations among different words in the sentence. Further, they proposed Skip-Tree CRFs to combine both above explained methods and use these trees to extract aspects and opinions from movie reviews by giving list of aspects as input seed. Later on, Chen et al. (2012) have improved this technique by integrating self-tagging process in order to minimize manual effort for labelling the data and in order to achieve the desired balance between algorithm complexity and accuracy, by identifying optimal set of learning functions. They applied many aspect extraction techniques to compare the accuracy of different systems at different levels and on the same dataset on product reviews.

Jakob and Gurevych (2010) also used the supervised CRF-based techniques to extract the opinion targets from reviews. They observed that, same word may have different representation in different domains, for example unpredictable may have positive in movie reviews but negative in car reviews. Therefore, they used the approach on different domains by keeping in mind such words which has domain portability. Furthermore, for the extraction opinion expressions and their attributes Choi and Cardie (2010) used a hierarchical parameter sharing technique using CRFs. They defined the problem as a sequence tagging task to identify both opinions and aspects. Their approach not only extracts opinions and aspects but also ranked the aspects according to the polarity of their opinion words.

Huang et al. (2012) also proposed a CRF-based probabilistic learning model to extract product aspects. The task of aspect extraction was adopted as sequence labeling task and CRF was used to tackle this task. The product aspects were divided into three sub-categories for learning process and certain tagging rules were defined to identify these aspects. After extraction of aspects, they defined two categories to group similar aspects. The first approach is based on WordNet, which finds the similarity calculations using WordNet dictionary approach, and second approach based on syntactic dependencies for long distance syntactic context. The combination of both approaches was used to place all the product aspects in their respective group.

Yang and Cardie (2013) proposed a method to jointly identify opinion related entities i.e. opinion expression, opinion targets and opinion holders along with relations which link the opinions with entities and these relations were IS-ABOUT and IS-FROM. They divided the whole task into multiple subtasks. The first task was to identify opinion and entity words and for this, they imply CRF to find the sequences among different words. As the opinion aspects were identified, the next step was to identify relations among different entities and opinions. To identify the relations, they proposed two classifiers Opinion-Arg relations and Opinion-Implicit-Arg relations. To identify these relations, they constructed candidate set of opinion expressions (opinion) and opinion arguments (aspect). First classifier identifies those relations where arguments are explicit and for those arguments which are implicit they used the second classifier. In the last phase, they join these methods with a number of constraints to find the opinion entities and opinion relations. They presented that the knowledge from different predictors can be integrated to achieve significant improvement in overall performance.

3.3.5 Semantic parsing

Li et al. (2012) formulated the opinion target extraction problem as a shallow semantic parsing problem. They applied this approach on datasets from two different domains i.e. university and web-services. In proposed shallow semantic parsing, the sentence was represented by a parse tree and a predicate was used to identify the corresponding semantic arguments in the sentence. They used several heuristic rules to map the opinion targets into several constituents and to prune out those arguments which do not satisfy the defined rules. To identify the valid argument from the remaining arguments, they adopt a binary classifier which not only targets the basic aspects but also focus on the additional.

4 Implicit aspects

Some of the implicit aspect's identification techniques have been discussed in Sect. 3 where researchers extracted explicit and implicit aspects simultaneously. On the other side, some researchers have taken the problem of implicit aspect identification as separately and proposed algorithm to deal with it. The most of the approaches based upon the explicit aspects and if any sentence some opinion word is found, the previous extracted explicit aspect is tracked and claimed as implicit aspect. While some have used association rule mining approach which grows exponentially with the problem.

Su et al. (2008) proposed a clustering method to map the implicit aspects in Chinese reviews. They used the sentiment words to map it to appropriate explicit aspect. The aspect hierarchy and sentiment terms were used to identify implicit aspects by Yu et al. (2011b). By defining a centroid for each aspect node in hierarchy, they calculated the cosine similarity between each centroid and implicit-aspect review and group them with the maximum similarity node.

Hai et al. (2011) proposed association rule mining approach to identify implicit aspects from Chinese reviews. They generate the association rules among explicit aspects and their opinion words which produce a co-occurrence matrix. In the second phase they clustered the explicit aspects and generate more robust rules. If in any sentence, they found opinion word but no explicit aspects, then they use these robust rules to identify the most appropriate match with the highest frequency.

Zeng and Li (2013) proposed a rule-based approach to extract explicit aspects and to identify implicit aspects; classification-based approach was proposed. These explicit aspects along with their opinion words were then clustered in appropriate classes. Finally, they used a set of opinion words and map them to clusters of explicit aspect and opinion words to identify the implicit aspects. Fei et al. (2012) proposed a dictionary-based approach, which tries to identify those nouns which are indicated by adjective opinion.

Zhang and Zhu (2013) proposed a novel co-occurrence association based method to identify implicit aspects from customer reviews. They performed the task in four steps: first they calculated the co-occurrence frequency for all the words in the corpus; determined the modification matrix using double-propagation approach which records the modification relationship among aspects and opinions; then they identified all the opinion words and selected all the aspects which could be modified by these opinion words; and in the last they choose the best implicit aspect not based on only opinion word but upon all the words present in the sentence.

Wang et al. (2013b) also proposed association rule-based hybrid approach to extract implicit aspects. They further extend these associated rules by adding substring, dependency and constrained topic model rules. Wang et al. (2013a) used topic modeling along with SVM to identify implicit aspects. Xu et al. (2015) used LDA to construct explicit topic model and then incorporating must-link, cannot-link and relevance-based prior knowledge with explicit topic model to extract implicit aspects.

Sun et al. (2014) proposed a context-based method to extract implicit aspects from Chinese product reviews. They performed the task in three stages, in first stage they identified the relationship among aspect and opinion words, in second step they searched for any implicit aspect and if found then generate the candidate set and in last step they used this candidate set to identify implicit aspects by calculating score between opinion words and implicit aspect's context information.

Schouten and Frasincar (2014) proposed a supervised method to identify implicit aspects from product and restaurant reviews. The algorithm they proposed first generates the list of implicit aspects on the bases of trained dataset, list of unique lemmas and their frequencies. As these lists were generated, the algorithm computes a score for each implicit aspect which is the ratio among co-occurrence of each word and frequency of the word. As the number of sentences containing implicit aspects is very low, therefor they defined a threshold to identify implicit aspects. Only those aspects will be identified which have the score greater than the given threshold.

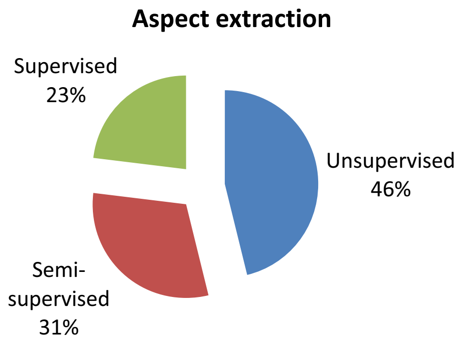

Fig. 3 Distribution of explicit aspect extraction approaches

5 Analysis and discussion

In this section, we have presented the comparison and analysis of aspect extraction approaches. The result's comparison is only for the explicit aspect extraction. For implicit aspects, there are no comparable results available and neither any benchmark with whom the results could be harmonized. Figure 3 shows the overall distribution of approaches, divided into three main categories and hence the analysis was conducted accordingly.

Most of the research has focused on the unsupervised and semi-supervised learning while not much researchers explored the supervised approaches. This is because of the laborious and time consuming task of training the dataset. On the other hand, unsupervised approaches do not required any trained set as input while semi-supervised need only few seed words to start the cycle. Still, large number of researcher have been attracted towards the unsupervised approaches and produced remarkable results which will be discussed shortly.

These approaches used different datasets, which belongs to diverse kind of domains and languages. Most of the work focused on English language datasets, but many researchers have conducted the experiments on domains belonging to Chinese language. The results of one domain cannot be compared with the results of other domains and similar constraint for the language. Therefore, this is necessary to identify the domains and languages of all the approaches to conduct a comprehensive and justifiable comparison. Figure 4 illustrates the domains followed in the studies. Experiments were conducted on 13 different domains but more than 50% of research has focused on product reviews only. In the chart, there are some solo product items like camera, cellphone, mobile, headphone and MP3 but when we are talking about product domain, it contains more than one product and hence cannot be compared with a single item.

Due to the large number of papers, diverse nature of datasets and divergent varieties of approaches, this would be almost impractical to plot a precise comparison among all the approaches. Therefore, to better understand the effectiveness of each approach, we have analyzed and summarized different approaches for each of the category separately, as mentioned in Fig. 3. Although, it would be unjustifiable to compare the results from the different domains but this can help to understand the contribution of each approach. As highlighted in Fig. 4, most of the research has focused on product domain, therefore, the domain is mentioned explicitly only with those approaches which used other than product domain for the experiments. If the domain is not mentioned then the results will be representing the product domain.

The experiments were reported by the researchers for different languages but most of them followed English language datasets. Therefore, approaches which used Chinese language

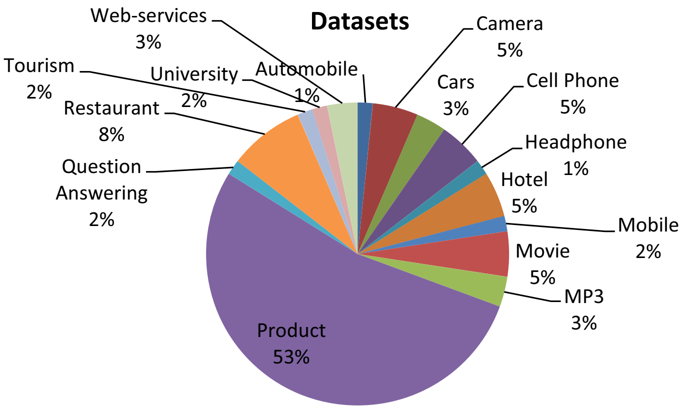

Fig. 4 Dataset domains used for aspect extraction

datasets were highlighted with a "*" and for Japanese language "+" sign has been used. Experimental results were collected from the references (Table 1, 2 and 3) which were in the form of Precision, Recall and F-measure. In some cases, authors did not provide all the outcomes, therefore, only those results were presented which were reported. Therefore, for some approaches only precision is available and for some F-measure. A number of studies had followed product review dataset (Hu and Liu 2004b, a) for aspect extraction and results comparison as shown in Fig. 8. Most of the studies concluded their comparison by comparing average calculations for precision, recall and F-measure. Therefore, to compare and summarize all the approaches, the average was calculated for those approaches which use the same dataset. Therefore, precision, recall and F-measure are the average calculations for the specified product domain. For other domains, the results are reported identically for each dataset and separated by "\" in Figs. 5, 6 and 7.

Figure 5 elaborates the results of different unsupervised approaches over different domains. FB1 shows a high precision rate with a low recall and F-measure. FBP reported remarkable F-measure but the study does not provide any recall and precision calculations and hence cannot be justified. From the figure, it is cleared that almost all the approaches have produced interesting results in the respective domain, but Opinion Zoom (OZ) reported very low accuracy. This is because of the tourism domains, where people like to tell stories for their experiences. In such cases, the number of objective sentences is much higher than the subjective sentences and therefore, yields a low performance. Also, IEDR could not produce good results for Chinese hotel reviews where it produced comparable results in product domain. For all the three measurements, Rule-based and SSPA produced better results than all the other approaches.

For semi-supervised approaches, Fig. 6 provides a rich picture of all the techniques. As compared to unsupervised approaches, semi-supervised approaches are trailed behind a little. Among all, semi-supervised approaches performed well on English reviews as compared to Chinese language reviews. Lexicon-FT reported a high precision but the recall and F-measure for this approach are not satisfactory. GP-based produced better results along with ASWAM and WAN as compared to other approaches. Semi-supervised techniques cannot perform better for Chinese language datasets as compared to some unsupervised approaches like WTM except BST3. Therefore, it creates a big gap to study new approaches for aspect extraction on Chinese language datasets.

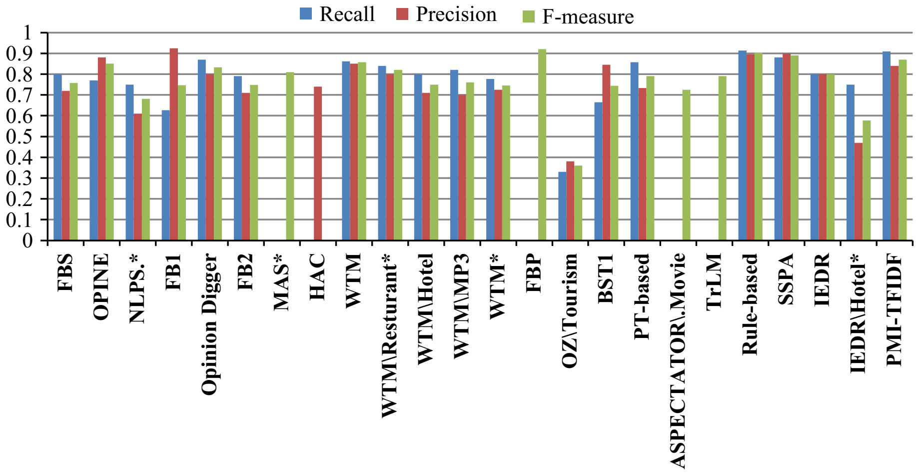

Fig. 5 Aspect extraction accuracy of unsupervised approaches

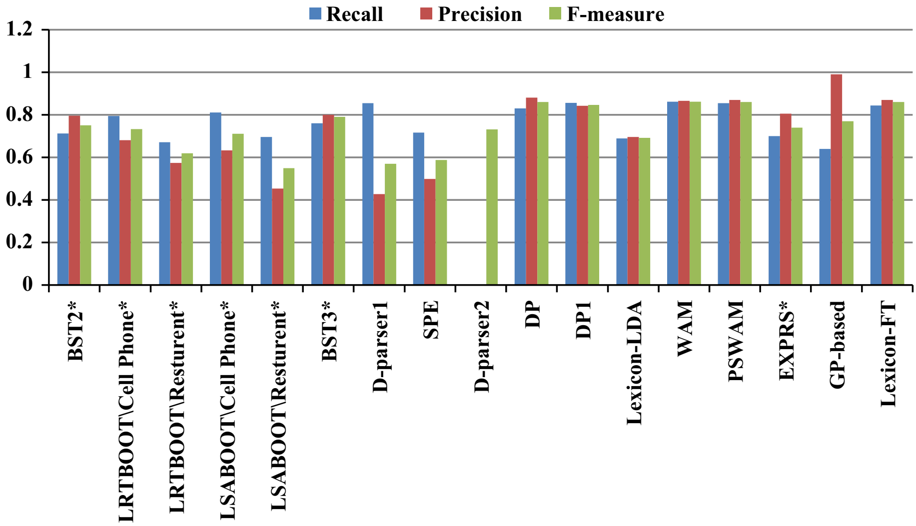

Fig. 6 Aspect extraction accuracy of semi-supervised approaches

Figure 7 elaborates the results of different supervised approaches. This is cleared from the figure that supervised approaches have produced better results as compared to semi-supervised approaches. But these results are comparable with the unsupervised approaches. On the other hand, unlike to supervised approaches, unsupervised approaches do not required any manually trained data as input and hence proved their significance in SA. Supervised approaches used most diverse nature of datasets as compared to unsupervised or semi-supervised approaches where most of the researchers have focused product domain datasets.

Figures 5, 6 and 7 plotted a comprehensive detailed analysis of different aspect extraction approaches. But this is difficult to decide which one performs better. This is because of different language and domain constraints. One language's approach cannot be compared with the approach of other language and similar different domain's results cannot be compared.

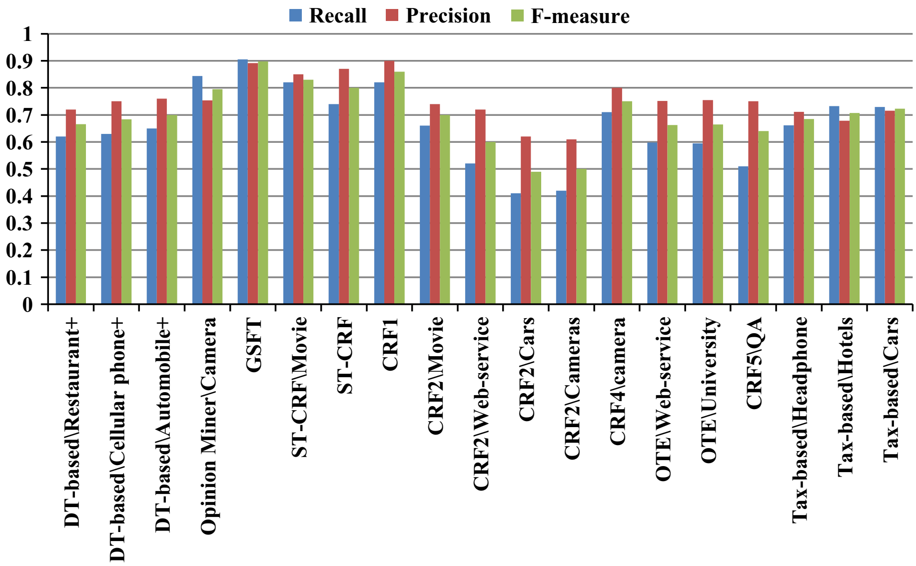

Fig. 7 Aspect extraction accuracy of supervised approaches

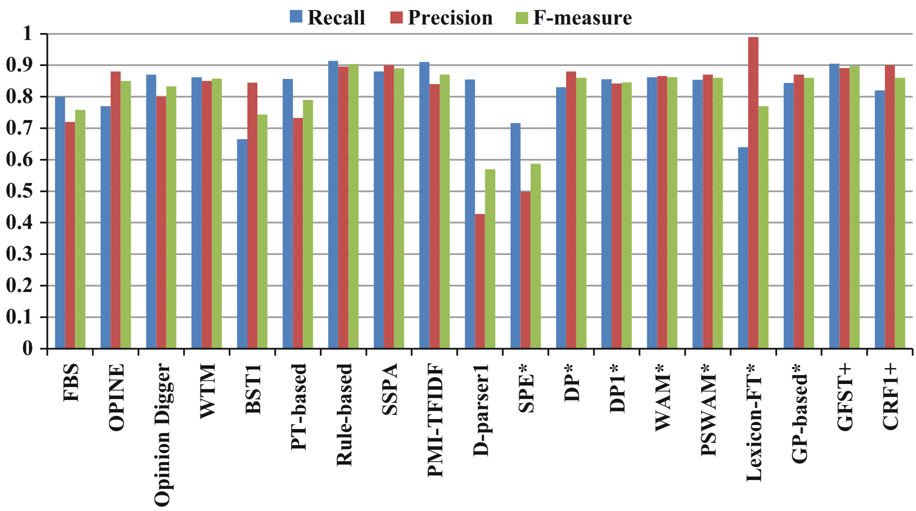

Fig. 8 Comparison of different approaches for customer review dataset

There is no mechanism to compare such diverse approaches and conclude a justified decision. But there are some approaches which adopted Customer review dataset[2] for the evaluation and comparison of their results which contains five different products reviews. Therefore, we have made a comparison of such approaches which used this dataset. Although majority of study focused on product reviews but not all of them used customer review datasets. Hence, not all approaches, which focused product domain, were selected but only those were chosen which used the same review dataset.

[2] www.cs.uic.edu/~liub/FBS/sentiment-analysis.html

In Fig. 8, the results of such all approaches, which used the same dataset for their experiments, are elaborated. The "*" sign represents the semi-supervised approaches and "+" for supervised approaches. The remaining are the unsupervised approaches. Although, Lexicon-FT has produced a very high precision, but the recall and F-measure are quite low. On the other hand, SSPA, Rule-based and GFST have produced most interesting results with respect to all three matrixes. Most of supervised and unsupervised approaches have produced better results. But among them all, unsupervised approaches have proved their importance and significance for aspect extraction. This is because for unsupervised approaches, there is no need for the trained dataset but supervised approaches heavily dependent upon user provided input which makes them laborious and time consuming.

6 Conclusion and future work

Aspect extraction is the most vital task in aspect-level SA and hence, studied by most of the researchers. The aspect extraction phase includes extracting explicit aspects and identifying implicit aspects. There are enormous amount of work for the extraction of explicit aspects but implicit aspects have not been studies vigorously. Therefore, this study focused on only these aspects and included only those papers which have presented with results. Although, topic modeling has also been adopted for the extraction of aspects, but due to unavailability of concise results, we have not included those techniques in this survey. Also, this survey has presented a detailed explanation and precise comparison and analysis of aspect extraction approaches for aspect-level SA. More than 60 research approaches are being summarized and categorized according to their complexity and nature. Due to the large number of approaches, explicit aspect extraction techniques are categorized sophistically into relative sections. Along with the explicit aspects, techniques for implicit aspect extraction are elaborated separately.

The meticulous comparative analysis demonstrated the importance of different approaches and impact of using different techniques on different language datasets from diverse type of domains. The analysis and comparison helped to identify gaps in the area of aspect-level SA. There is no work available, in this survey, which used supervised learning in the domain of Chinese language datasets. Also, semi-supervised approaches did not perform well for such datasets. Therefore, there is a need to explore supervised approaches to solve the problem using Chinese language domains. It was also observed that, some approaches produced higher precision for a specific domain but low recall, on the other-hand, some approaches produced higher recall with low precision. Therefore, combination of different approaches can yield better results. There are number of problems which need to be identified and focusing their solution can make the area of aspect-level SA more pervasive.

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