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360 degree view of cross-domain opinion classification: a survey

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Abstract

In the field of natural language processing and text mining, sentiment analysis (SA) has received huge attention from various researchers' across the globe. By the prevalence of Web 2.0, user's became more vigilant to share, promote and express themselves along with any issues or challenges that are being encountered on daily activities through the Internet (social media, micro-blogs, e-commerce, etc.) Expression and opinion are a complex sequence of acts that convey a huge volume of data that pose a challenge for computational researchers to decode. Over the period of time, researchers from various segments of public and private sectors are involved in the exploration of SA with an aim to understand the behavioral perspective of various stakeholders in society. Though the efforts to positively construct SA are successful, challenges still prevail for efficiency. This article presents an organized survey of SA (also known as opinion mining) along with methodologies or algorithms. The survey classifies SA into categories based on levels, tasks, and sub-task along with various techniques used for performing them. The survey explicitly focuses on different directions in which the research was explored in the area of cross-domain opinion classification. The article is concluded with an objective to present an exclusive and exhaustive analysis in the area of opinion mining containing approaches, datasets, languages, and applications used. The observations made are expected to support researches to get a greater understanding on emerging trends and state-of-the-art methods to be applied for future exploration.

Keywords Opinion mining · Sentiment analysis · Cross-domain opinion classification · Domain adaptation · Transfer learning · Machine learning

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1 Introduction

In the present time, the Internet plays an important role in people's life. With the help of the latest technologies, people can access, share, and generate content over the Internet. In the World Wide Web, Web 1.0 refers to the first generation, which was entirely made up of web pages connected by hyperlinks and people can explore a website, read the content of the pages, but cannot write or add anything on the web page. Internet users are moving from Web 1.0 to Web 2.0 since 2004. Web 2.0 ("Interactive Web" or "The Social Web") explains a novel stage of web facilities, social websites, and applications with an increasing emphasis on user collaboration (User-generated content and the read–write web). People are consuming as well as contributing information through sites such as YouTube, Flickr, Digg, blogs, etc. Web 3.0 ("web of meaning" or "the Semantic Web") refers to the third generation of the World Wide Web. Web 3.0 includes smart search and behavioral advertising along with Web 2.0 features. Web contents are unstructured, structured, semi-structured, wrongly spelled and noisy that required Natural Language Processing techniques to analyze the data.

Social networking sites play an important role in Internet activities. Internet users and Internet content are increasing day by day. People are excited to share and express their feelings on any issues and day-to-day activities on the Internet. The micro text or short text is the biggest challenge in text analysis and different approaches are utilized for micro text normalization (Satapathy et al. 2020; Cambria 2016). Due to the explosive progress of online activities on the Internet (conferencing, chatting, social media communication, ticket booking, surveillances, e-commerce, online transaction, micro-blogging, and blogging, etc.) leads us to load, transmute, extract, and analyse the very large extent of data that is referred to as Big Data. This large amount of data can be analysed in several real-life applications by using a combination of data mining, text mining, web mining, and information retrieval techniques. Several blogs, forums, e-commerce websites, additional web resources, news reports, and social networks work as platforms to express views, which can be used to observe or report the feelings of the customer and general public on public occasions, organisations plans, monitoring reputations, political activities, promotion campaigns and product preferences (Ravi and Ravi 2015). A huge amount of raw data is tough to analyse and needs extant methods to get a comprehensive review summary. The population of the world and Internet users is going to increase day by day. People are giving more attention to web 1.0 and web 2.0 and many activities are performed by Internet users as shown in Fig. 1 (Balqisnadiah 2016).

User-generated views are the main source of raw text. With the rapid progress of user-generated typescripts on the web or the Internet, mining of valuable data automatically from plentiful documents receives more research interest in numerous areas of Natural Language Processing (*NLP*) (Sun et al. 2017). The concept of artificial intelligence is used everywhere example Amazon's Alexa from phone to devices. Nowadays machine learning methodologies or technologies are increasingly used in artificial intelligence fields. The concept of artificial intelligence together with a large amount of data is used by many different companies (Netflix, Google, data companies, etc.). NLP focuses on smartphones the human language to explain insight, help in human text and many more. The everyday human says several words to other people that interpret in countless meanings because every word is context-dependent. NLP is used for many prospectives such as word suggestion, a quick compilation of data, voice to text converter (Google assistant, Alexa application, Search engine optimization (*SEO*) application, handwriting recognition (online and

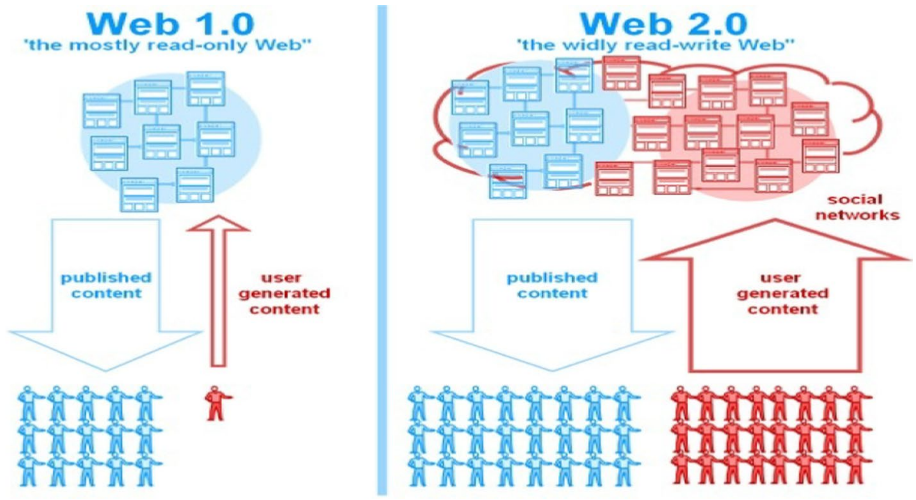

Fig. 1 Web 1.0 and Web 2.0 (Balqisnadiah 2016)

offline), speech recognition system, opinion mining, etc. The Computational study of a person's thoughts, moods, reviews, feelings, emotions, events, appraisal, issues, attitude, and topics are defined in sentiment analysis. The following text, explain the early reviews in the field of sentiment analysis.

1.1 Sentiment analysis: the earlier reviews

In the field of sentiment analysis (Pang and Lee 2008) reviewed and analyzed more than 300 research articles by covering the major tasks (opinion summarization, opinion classification, sentiment mining, polarity determination, opinion spam detection, different level of sentiment analysis, etc.), challenges and applications of opinion mining. Later, Tang et al. (2009) highlighted some issues in the field of sentiment analysis or opinion mining such as sentiment extraction, document opinion classification, word opinion classification, and subjectivity classification. Further, the authors specified some approaches for the subjectivity classification such as a cut-based classifier, multiple Naïve Bayes classifier, Naïve Bayes classifier, and similarity dependent.

O'Leary (2011) reviewed on blog mining and outlined different kind of blog search, forums, sentiments to be analysed and their applications. Montoyo et al. (2012) mentioned applications, attainments and some open issues in the field of sentiment mining and subjectivity classification. Tsytsarau and Palpanas (2012) focused on opinion spam detection, contradiction analysis, opinion aggregation, and opinion mining. The authors equated different opinion mining techniques and approaches that are applied in a common dataset.

Liu (2012) surveyed more than four hundred research articles in the area of opinion mining and sentiment classification. This survey covered NLP issues, sentiment analysis applications, sentiment lexicon and its issues, different levels of analysis, opinion summarization, cross-domain sentiment classification, cross-lingual sentiment classification, aspect-based sentiment analysis, sentence subjectivity classification, quality of reviews, sentiment lexicon generation, and some challenging issues in the field of opinion classification and sentiment analysis.

Feldman (2013) studied in the field of sentiment analysis and pointed-out some specific difficulties: sentiment lexicon acquisition, comparative sentiment analysis, sentence-level sentiment classification, document-level sentiment classification, aspect-based sentiment classification and some open challenging issues such as sarcasm detection, automatic entity recognition, discussion on multi-entity in the same review, and composition statement's in sentiment analysis. Cambria et al. (2013) the survey focused on complexities involved in opinion mining, concerning demand and future direction.

After that Medhat et al. (2014) focused on the problem of sentiment analysis concerning the techniques not the applications' point of view. The author categorized the article according to the techniques involved and classified the various techniques of sentiment analysis with brief details of algorithms. The author explained the available datasets and categorized the datasets according to the applications. Finally, discussed some sentiment analysis fields for enhancement such as transfer learning, building resources, and emotion detection. At last briefed fifty-four research articles listing out task accomplished, type of language, data source, polarity, data scope, algorithm utilized and domain-oriented.

Later, Ravi and Ravi (2015) reviewed about 251 research articles during (2002–2015) and classified the survey based on opinion mining approaches, applications, and tasks. This literature covered different tasks of sentiment analysis and pointed-out major issues in sentiment classification, review spam detection, degree of usefulness measurement, subjectivity classification and lexicon creation. Finally briefed thirty-two publicly available datasets and one hundred sixty-one research articles in the tabular form listing out concepts and techniques utilized, type of language, polarity, type of data and dictionary.

Further, Hussein (2016) identified challenges relevant to the techniques and methods in the area of opinion mining. Based on two-comparisons among forty-seven research articles, the authors discussed the effects and importance of opinion mining challenges in opinion evaluation. Finally summaries sentiment challenges and how to improve the accuracy based on previous work. After that, Al-Moslmi et al. (2017) studied about 91 research articles from 2010 to 2016 in the field of cross-domain sentiment classification. This study focused on the techniques, algorithms, and approaches used in cross-domain opinion classification. Further, highlighted some open issues in cross-domain opinion classification. Finally summarized the methodologies and findings of twenty-eight research articles in the area of cross-domain opinion classification. It is observed from the survey analysis that there is no perfect solution found in cross-domain opinion mining.

Recently, Sun et al. (2017) reviewed opining mining using the techniques of NLP. Firstly, the authors explained information fusion techniques for combining information from multiple sources to solve certain tasks. This study also presented some natural language processing techniques for text processing. Secondly introduced the different approaches, methods, and resources of sentiment analysis for different levels and situations. The aim of opinion mining is to extract the sentiment orientation (positive or negative) from different levels of sentiment analysis (sentence level, document level, fine-grained level, word level, etc.) using supervised, unsupervised and semi-supervised learning methods. Finally discussed some advanced topics (opinion spam detection, review usefulness measurement, opinion summarization, etc.), some open problems (annotated corpora and cumulative errors from pre-processing) and some challenges (deep learning for accuracy) in the field of opinion mining. Most recently Young et al. (2018) explained the latest trends of deep learning in NLP, compared various deep learning models and explained the past, present and future of deep learning in NLP.

This literature survey diverges from earlier review articles in several ways such as (1) categorized the standing studies based on different tasks in sentiment analysis and different level of sentiment analysis, (2) this study emphasized the cross-domain sentiment classification that is one of the most challenging tasks in sentiment analysis (3) summarized different tasks of sentiment classification in some aspects (approaches, techniques or methodologies, datasets, lexicon or corpus, and type of languages are utilized in sentiment classification), (4) this study provides a detailed list of publically available toolkits and supported language by toolkits for sentiment analysis' tasks, (5) summarized a detailed list of available datasets, data sources, annotated corpora, and sentiment lexicons along with type of languages that is utilized in the field of sentiment analysis, (6) classified the baseline methods and research articles of cross-domain opinion classification in four aspects (approaches and methods utilized, datasets and languages used, name of the corpora or dictionary utilized and details description of research article) (7) study discussed some challenging issues, open problems and future directions in the area of sentiment analysis (8) summarized one hundred plus research articles of sentiment analysis in the aspect of techniques, methodologies, datasets, data source, and type of language.

The main aim of this survey paper is to understand the different techniques, approaches, and datasets, used in the field of sentiment analysis to achieve accuracy. Rest of the article is organized as follows: Sect. 2 explains the sentiment analysis and different levels of sentiment analysis. Section 3 presents different tasks and sub-task of sentiment analysis, state-of-the-art discussion on opinion mining along with publicly available datasets/lexicon and toolkits. Section 4 explains one of the most challenging tasks of sentiment classification named cross-domain opinion classification. Sections 5 and 6 covers the outcomes from the survey, the pros and cons of different baseline methods, challenges, open issues and future direction in the field of sentiment analysis. Section 7 concludes the survey.

2 Sentiment analysis

Sentiment analysis is a computational study of people's views or aspects towards an entity. Here entity can be an individual thing like topics, blogs or events. The term sentiment analysis was firstly introduced in early of this century and has become an active field for research. According to the definition of sentiment (Liu 2012), it is represented as a quintuple.

Definition of sentiment analysis (e_i, a_{ij}, s_{ijkl}, h_k, t_l), where e_i represents the i^{th} entity, a_{ij} represents the j^{th} aspect of the i^{th} entity, h_k represents the k^{th} sentiment holder, t_l represents the time when the sentiment conveyed and s_{ijkl} represents the sentiments on aspect a_{ij} of entity e_i at t_l time for h_k opinion holder. The sentiment or opinion s_{ijkl} is neutral, positive or negative.

For Example, "*The Power backup of a power bank is excellent!*" Here "*Power bank*" represents an entity, "*Power backup*" represents as aspect, and the sentiment expressed as positive.

Sentiment analysis examines the people's moods, aspects, views, opinions, attitudes, feelings, and emotions towards entities (services, products, researches, political issues, organizations, random issues, and any topics). Sentiment analysis aims to find the polarity. Polarity can be positive, negative or neutral towards the entity.

Machine learning, lexicon-based, and hybrid approaches play an important role in sentiment analysis for obtaining the polarity. Sentiment analysis can be used in different applications such as movie sale prediction, market prediction, recommender system, customer satisfaction measurement and many more for achieving one goal i.e., opinion analysis of people's reviews. Due to rapid growth and interest in e-commerce, this is one of the prominent sources of analyzing and expressing their opinions. Opinions are important for both sides: customers as well as the manager's point of view. Many customers take their decision based on reviews that are available on the Internet. Sentiment analysis is a multifaceted problem, not a single problem. Texts for sentiment analysis are coming from various sources in diverse formats. Various pre-processing steps are needed to perform the task of sentiment analysis. Sentiment analysis helps in achieving various tasks such as sentiment classification, spam detection, usefulness measurement, subjectivity classification, and many more. Data pre-processing and acquisition are the most common subtask required for text classification and sentiment analysis, which are explained in the Fig. 2. The next subpart of this section explains the different levels of sentiment analysis i.e., document, sentence and aspect level.

2.1 Levels of sentiment analysis

In general, sentiment analysis has been classified at three different levels such as document level, sentence level, and entity/aspect level. Some studies explain the concept of user-level and concept-level sentiment analysis also as shown in Fig. 3. Concept-level sentiment analysis emphasized on semantic analysis of the text by using semantic networks (Cambria 2013). User-level sentiment analysis analyze the opinion expressed in individual texts (what people think) (Tan et al. 2011). A brief explanation of these levels of sentiment analysis is presented below.

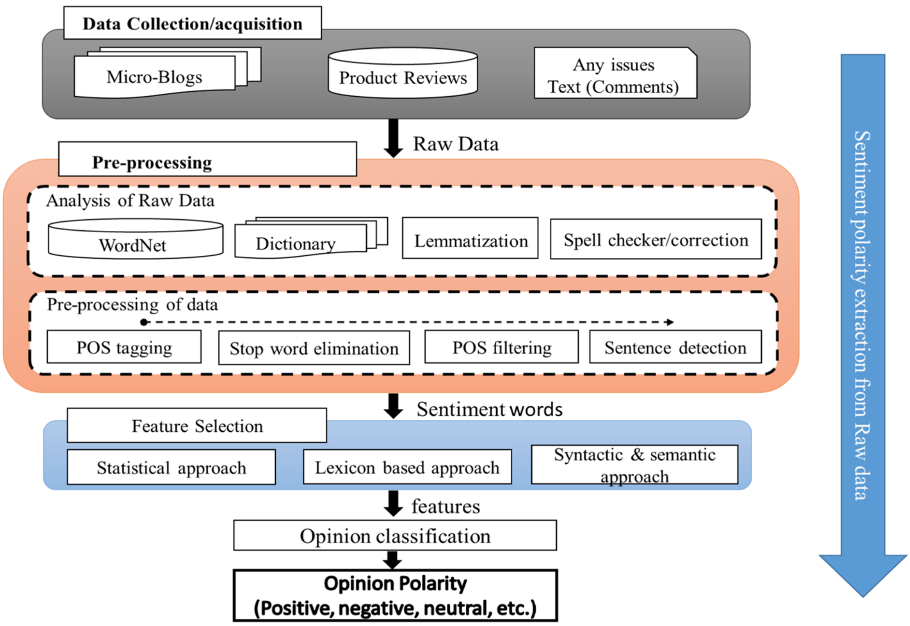

Fig. 2 Process of sentiment analysis

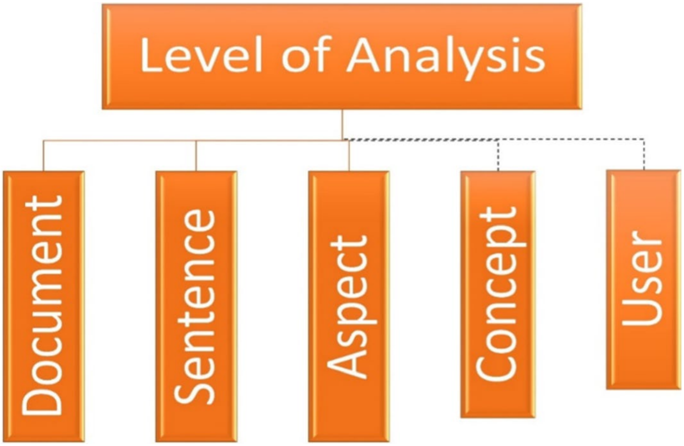

Fig. 3 Levels of sentiment analysis

2.1.1 Document-level sentiment analysis

The main task of document-level sentiment analysis is to find out the overall opinion polarity of the document such as blogs, tweets, movie reviews, institute reviews, product reviews, and any issues. The objective of the document-level sentiment analysis is to determine the third tuple from the quintuple as per the definition of sentiment analysis. The generalized framework of document-level sentiment analysis is explained in Fig. 4. Research articles of document-level sentiment analysis are summarized below in Table 1.

In document-level sentiment analysis (Moraes et al. 2013) utilized some machine learning approaches such as Support Vector Machine, Neural Network, and Naïve Bayes for comparison on product reviews in the English language. Du et al. (2014) utilized neural network and SVM on microblogs (Box office) in the Chinese language. Geva and Zahavi (2014) used neural network, decision tree utilized a stepwise logistic regression, genetic algorithm, and SVM on the stock market and news count in the English language. Xia et al. (2011) utilized Maximum entropy, Naïve Bayes, SVM on product reviews in the English language. Lin and He (2009) proposed a new unsupervised learning approach that is based on Latent Dirichlet Allocation (LDA) named as joint sentiment topic. Li et al. (2007) proposed a framework named Dependency-Sentiment-LDA. With the help of the Markov model, the author assumes the sentiment of words that depends on the previous one. In document-level sentiment analysis, the word sentiment information is consistent with the labeled document (Li et al. 2017). For each document, determined the topics and sentiments simultaneously. Irrespective of the research conducted in the area of document-level sentiment analysis, areas such as opinion mining, usefulness, and opinion spam detection remain a challenge.

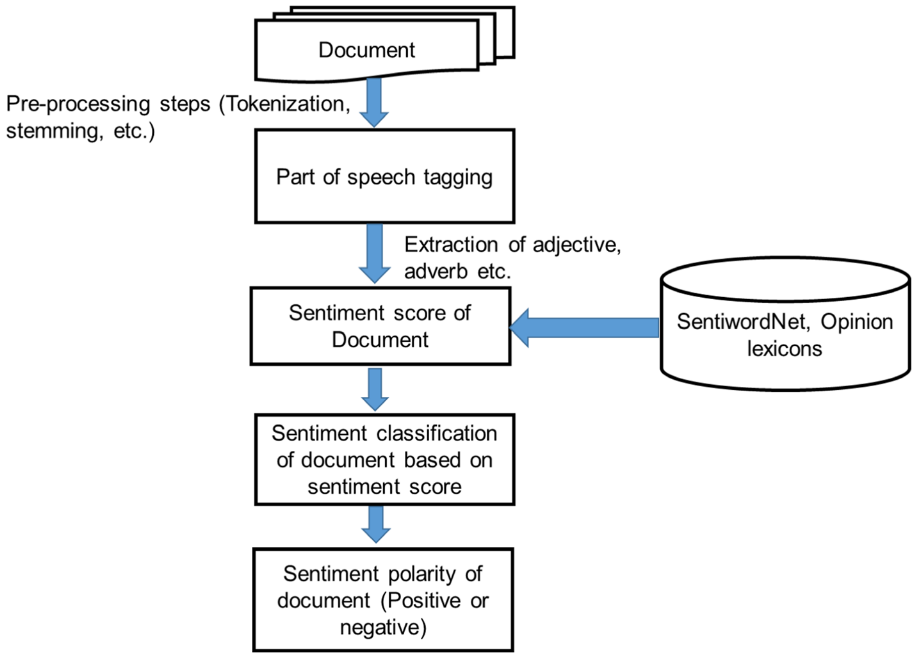

Fig. 4 Process of document-level sentiment analysis

2.1.2 Sentence-level sentiment analysis

Sentence-level sentiment analysis is similar to the document-level sentiment analysis, subsequently, a sentence can be observed as a short document. The objective of sentence-level sentiment analysis is to categorize the opinion expressed in each sentence. Before analysing the polarity of a sentence, find out whether the sentence is objective or subjective. If the sentence is subjective then find out the orientation or polarity (positive or negative) of the sentence. The process of sentence-level sentiment analysis is shown in Fig. 5. Research studies in sentence-level sentiment analysis are summarized in Table 2.

The applications of sentence-level SA in opinion mining are multi and cross-lingual, review spam detection, polarity detection, etc.

2.1.3 Aspect-level sentiment analysis

Classifying text at the sentence-level or the document-level provides valuable information in several applications but some time that information is not sufficient in many advanced applications. To acquire this information from the opinionated text, we need to go at aspect level which receives a great interest in research. In aspect-level, several variations are included like word (also known as an entity, attitude, or feature) and concept-level sentiment analysis. According to the definition of sentiment analysis, the first three components in quintuple (entity, aspect, sentiment) discover aspect level sentiment analysis and

Table 1 Document-level sentiment analysis literature compilation

References	Approaches/techniques	Dataset language	Dataset/Corpora	Details
Yessenalina et al. (2010)	Support vector machine (*SVM*) with latent explanations and proximity features	English	U.S. Congressional floor debates and movie reviews	To achieve the task of document-level SA, proposed a joint two-level latent variable structured models and obtain the overall polarity of the document
Bollen et al. (2011)	Linear regression, self-organization fuzzy neural network, dictionary-based method	English	Dow Jones Industrial Average (DJIA), micro-Blog (stock market prediction)	Utilized two mood tracking tools for analyzing the tweets' name as GPOMS (Google-Profile of Mood States) and opinion finder (OF)
Moreo et al. (2012)	Dictionary-based approach, Lexicon based approach	English	News reviews	Proposed a lexicon-based approach, to achieve the polarity and orientation of user comments on the news
Bosco et al. (2015)	Cohen's κ-coefficient, Blogmeter's techniques	Italian	Micro-Blog (Tweets on political opinion)	In order to study the irony, Sarcasm and sentiment words for the Italian language, the author introduced the Senti–TUT Twitter corpus and utilized Cohen's κ-coefficient, Blogmeter's techniques
Pang et al. (2002)	Maximum entropy, SVM classifier + POS Tag, unigram, bigram, position feature, naïve Bayes	English	Movie review	Employed the machine learning algorithm for sentiment analysis and suggested the traditional topic-based categorization that performs well as compared to this approach
Turney (2002)	Pointwise mutual information and information retrieval (PMI-IR)	English	Multi-domain (movie, automobiles, etc.)	The author used unsupervised learning approach along with PMI-IR algorithm and follow these steps, 1. POS tag-extract adjective and adverb 2. Use PMI-IR for calculating the semantic orientation 3. Classification of review
Kennedy and INkpen (2006)	SVM	English	Movie review	The author used two techniques General Inquirer and SVM, in order to determine the sentiments on movie review

Table 1 (continued)

References	Approaches/techniques	Dataset language	Dataset/Corpora	Details
Pang and Lee (2004)	Naïve Bayes and support vector machine	English	Movie review	Utilized Graph Cut Based Classification for Subjectivity extraction of the sentence
Taboada et al. (2011)	Lexicon based approach (dictionary-based approach)	English	Product review	The authors used the semantic orientation calculator to determine the semantic orientation (strength and polarity) of dictionaries of words
Wang and Manning (2012)	SVM, Multinomial Naive Bayes (MNB), SVM with Naïve Bayes features (NB-SVM)	English	Multi-Domain (movie, customer review, etc.)	The experiment results are showing that Multinomial Naive Bayes is better at snippets, SVM is better at full-length reviews and NB-SVM is a robust performer
Dasgupta and Ng (2009)	Spectral clustering algorithm, Support vector machine	English	Multi-domain (movie, kitchen, book, etc.)	Firstly, the author identifies the unambiguous reviews using a spectral clustering algorithm after that they applied the active learning to label the uncertain review. At the last, they trained the transductive SVM classifier based on the labeled review. The results are showing improvement
Cho et al. (2014)	Lexicon based approach (dictionary-based approach) and a new proposed algorithm	English	Multi-domain (movies, smartphones, and books)	Presented the data-driven approach for adjusting opinion dictionaries in various domains
Taddy (2013)	Multinomial inverse regression, active learning	English	MicroBlog (tweets on the political issue)	Maximizing the sampling efficiency
Li and Shiu (2012)	Diffusion mechanism, influence model, preference analysis	Chinese	MicroBlog (social advertising)	The model could explain advertisers with appropriate goals for diffusing advertisements and efficiently improve advertising usefulness

Table 1 (continued)

References	Approaches/techniques	Dataset language	Dataset/Corpora	Details
Dang et al. (2010)	SVM, semantic orientation	English	Products review (digital camera, book, DVD, kitchen appliances, electronics)	The experiments are performed on different feature sets and got comparable results

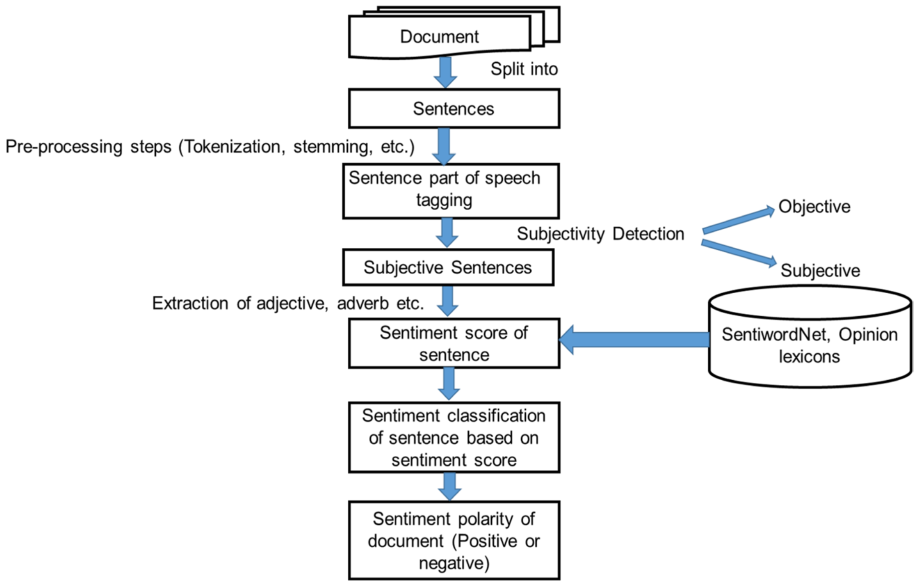

Fig. 5 Process of sentence-level sentiment analysis

categorized the opinion with respect to the particular aspects of entities. Aspect-level sentiment analysis aims to determine the particular targets (entities or aspects) and the corresponding polarities.

For example, "iPhone is made by Apple company. The iPhone's picture quality is very clear".

First, the comment is splitted into sentences such as ['iPhone is made by Apple company.', 'The iPhone's picture quality is very clear. '].

Secondly, the sentence is splitted into words such as ['iPhone', 'is', 'made', 'by', 'Apple', 'company', '.'] and next sentence as ['The', 'iPhones', 'picture', 'quality', 'is', 'very', 'clear', '.'].

Now each word is tagged along with POS taggers such as [('iPhone', 'NN'), ('is', 'VBZ'), ('made', 'VBN'), ('by', 'IN'), ('Apple', 'NNP'), ('company', 'NN'), ('.', '.')] and [('The', 'DT'), ('iPhone's, 'JJ'), ('picture', 'NN'), ('quality', 'NN'), ('is', 'VBZ'), ('very', 'RB'), ('clear', 'JJ'), ('.', '.')].

The entity, aspect, and sentiment are identified from both sentences, for instance from the first sentence, entity: "iPhone", aspect: "made by apple company" and sentiment: "neutral" is extracted. The sentiment is neutral as the sentence is objective and it reflects the universal truth.

From the second sentence, entity: "iPhone", aspect: "picture quality very clear" and sentiment: "express some sentiment as this sentence is subjective in nature and reflects the sentiment toward the quality of the iPhone.

Now, assign sentiment of aspect based on the polarity of aspect using a dictionary, statistical, lexicon and some other approach.

Finally, the sentence is classified into a positive or negative class based on assigned sentiment at the aspect-level.

The subsequent part summarizes the process of aspect-level SA in Fig. 6 along with current research work on aspect-level sentiment analysis is shown in Table 3.

Table 2 Sentence-level sentiment analysis literature compilation

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Farra et al. (2010)	Lexicon based approach, grammatical syntactic approach, semantic orientation	Arabic texts	Arabic movie reviews	Investigated two approaches, firstly grammatical syntactic method that employs the use of a common organization for the Arabic sentence and second semantic method with learning dictionary
Maks and Vossen (2012)	Lexicon based approach, dictionary-based approach	Dutch	Global data	Presented a lexicon model for the explanation of part of speech words like nouns, adjectives, and verbs used in opinion mining. The author used Dutch WordNet for lexicon creation
Yu and Hatzivassiloglou (2003)	Multiple naïve Bayes classifiers, naïve Bayes classifier, sentence similarity	English	Newswire articles	Explained three subjective classification approach based on sentence-level opinion mining. The author utilized Multiple naïve Bayes classifiers, naïve Bayes classifiers, and sentence similarity to train our classifier and POS tags, unigram, bigram, trigram, and count of opinion words to create the feature sets
Kim and Hovy (2004)	Lexicon based approach	English	Random data	Used a dictionary-based approach for the opinion holder and sentiments
Tackstrom and Mcdonald (2008)	Hybrid model (cascaded model, interpolating likelihood functions)	English	Multi-domain amazon data set (books, electronics, music)	This model presented a combination of less supervised sentence labels and fully supervised document labels. Results showing improvement as compared to all baseline methods

Table 2 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Yang and Cardie (2014)	Posterior regularization in the context of conditional random field	English	Customer review (cell phone and camera and multi-domain amazon data set (books, electronics, music)	A new approach introduced named posterior regularization in the context of the conditional random field for sentence-level opinion mining. Results showing improvement from state-of-art
Tang et al. (2015)	Joint segmentation and classification framework	English	Microblogs (Twitter data set)	The proposed framework joint segmentation and classification for sentence segmentation model and sentence-level opinion mining. Results showing improvement as compared to all baseline (SVM with n-gram, naïve Bayes SVM, lexicon-based classifier, sentiment-specific word embedding, etc.) methods
Narayanan et al. (2009)	SVM, LIBSVM implementation with a Gaussian kernel	English	User forum (medicine, audio system, automobile, LCD TV, and cell phone	The focused on the conditional sentences and find the polarity of the conditional sentence
Boiy and Moens (2009)	SVM, active learning, NB, Multinomial Naïve Bayes, maximum entropy, cascaded and aggregated learners	English, Dutch and French	User forum, blog, product review	The experimental results are showing better performance in SVM and maximum entropy classifiers with a combination of unigram and subjectivity feature selection

Table 2 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Desmet and Hoste (2013)	SVM, bootstrap resampling	English	Suicide notes	The author used 15 different emotions that indicate suicide behaviour and different features such as Lemmas, Lemmas + POS tags, pruned lemmas + POS tags, trigrams, WordNet synsets, SentiWordNet information, subjectivity clues for their experiments. The experiment results show that features execute good for frequent emotions, but not perform well for sparse data or rare emotions
Liu et al. (2013a, b)	Association rule mining (POS tags), Association miner classification based on Associations, preference and opinion-based recommendation (PORE) algorithm	Chinese	Product reviews	Introduced a new algorithm for features and opinion extraction based on the characteristic of review
Abdul-mageed et al. (2013)	SVM^{light}	Arabic	Blogs, newspaper text, Wikipedia talks, forum, microblog	A Supervised Machine Learning approach named SAMAR used in Arabic social media genres for subjectivity and sentiment analysis (SSA)

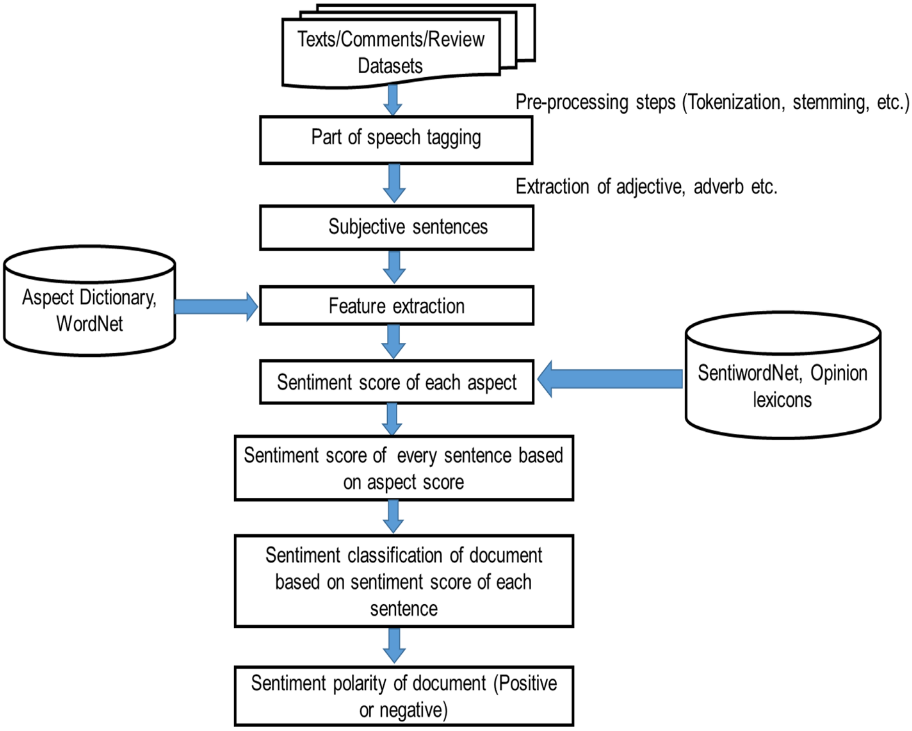

Fig. 6 Process of aspect-level of sentiment analysis

The lack of annotated corpora at feature-level and complicated appearance of sentiments are the problems in the aspect-level sentiment analysis (Ravi and Ravi 2015). The applications of aspect-level sentiment analysis in opinion mining are polarity determination, entity recognition, feature extraction, etc. The next section explains the different tasks, approaches, and methods of sentiment analysis and utilizes the different level of sentiment analysis to achieve the objective of tasks.

3 Different tasks of sentiment analysis

In general, sentiment analysis is used to perform multiple tasks. This article consists of some important tasks of sentiment analysis as presented in Fig. 7 like subjectivity analysis, spam review detection, degree of usefulness measurement, opinion summarization, aspect selection, sentiment lexicon creation, and opinion classification. Some task is further categorized into subtasks such as opinion classification is divided into polarity extraction, cross-lingual and multi-lingual opinion analysis, and cross-domain opinion classification. In this section, discuss all the tasks, sub-tasks, and approaches, methods, or techniques applied in the respective task as explained in Fig. 7a, b. Applied methods are generally categorized into four approaches such as lexicon-based, machine learning, deep learning, and hybrid approaches that are further classified into

Table 3 Aspect-level sentiment analysis literature compilation

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Zhou and Song (2012)	Maximum entropy, Part-of-Speech Latent Dirichlet Allocation (POS-LDA)	English	Movie review and trip advisor data	Proposed a new approach Part-of-Speech LDA along with several feature selection techniques for aspect-level sentiment analysis
Hu and Liu (2004)	Lexicon based approach, Association miner Classification Based on Associations	English	Digital camera, MP3 player, DVD player	The author performed multiple tasks along with aspect-level sentiment classification like text summarization, sentiment classification, and opinion sentence identification
Agrawal and Srikant (1994)	Apriori, AprioriTid and lexicon-based approach	English	DB2/6000, DBS/MVS, AIX file system, real customer data	Introduced two new algorithms named as Apriori and AprioriTid. The experiment results showing that the proposed approach outperforms SETM and AIS
Li et al. (2012)	Page rank, Gradient descent, double propagation-based linear regression (DPLR), Linear regression	English	Product review (hotel, phone, and laptop)	Introduced a new approach named double propagation-based linear regression having two stages of work. In the first stage, they extract the features and sentiments using the double propagation. In the second stage, they rank the features using the linear regression method
Popescu and Etzioni (2005)	OPINE with relaxation labeling and Pointwise Mutual Information Statistics	English	Product review and hotel review	The author proposed a new approach OPINE with relaxation labeling for semantic orientation and achieve 22% higher precision compared to previous work
Qiu et al. (2009)	Lexicon based approach (dictionary-based approach), double propagation, and prop-dep	English	Product review (digital camera, MP3 player, DVD player)	The double propagation algorithm introduced to find the pair of sentiment targets and sentiment words. On the large and small data set, double propagation does not perform well

Table 3 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Miao et al. (2009)	Association Miner Classification Based on Associations (CBA), Lexicon based approach, temporal opinion quality	English	Product review (camera)	Suggested an opinion mining and retrieval system which aim is to extract knowledge from product reviews by employing information retrieval and data mining technology
Peñalver-martinez et al. (2014)	Lexicon based approach (ontology, dictionary-based approach)	English	Movie Review	The proposed approach takes advantage of SentiWordNet to expand feature-based opinion mining
Saleh et al. (2011)	SVM, Binary Occurrence (BO), n-gram, Term frequency-Inverse document frequency (*TF-IDF*) and Term Occurrence (TO)	English	Product review (Camera) 'Sistemas INteligentes de Accesoa la Información (SINAI corpus)	New corpora introduced named SINAI and compare them with different corpora that are available for research in sentiment analysis. The author utilized the Support Vector Machine with different features and weighting schemes
Chen et al. (2012)	Association rule mining, Conditional random fields (*CRF*), Lexicalized Hidden Markov Model (L-HMMs)	English	Product review (camera)	Compared the different sentiment analysis methods such as the Rule-based method as a baseline, Lexicalized Hidden Markov Model (L-HMMs), ASM, ASM + linguistic rule and CRFs based approach. CRFs outperforms relative to other methods
Dang et al. (2010)	SVM, Semantic orientation	English	Products review (digital camera, Book, DVD kitchen appliances, electronics)	The experiments performed on different feature sets
Gindl et al. (2013)	Rule-based approach, linguistic rules	English	Product review (mobile phone, camera)	Utilized the linguistic rule and rule-based approach for aspect extraction in sentiment analysis

Table 3 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Brody and Elhadad (2010)	Lexicon based approach, Local Latent Dirichlet Allocation (L-LDA)	English	Online review	The author introduced an unsupervised system for mining features and determining opinion in text. The approach is modest and simple (concerning language and domain) and considered the stimulus of words for opinion polarity
Zhai et al. (2011a)	Labeled-Expectation Maximization (L-EM) algorithm	English	Product review (car, mattress, insurance, vacuum, and home theatre)	A new algorithm introduced labeled-expectation maximization that outperforms all the other baseline algorithms
Ding et al. (2009)	Conditional random fields (CRF), Entity Discovery and EI	English	Howard Forums (Mobile phone) and AVS forums (Plasma and LCD TVs, Projectors and DVD players)	To the mining of comparative sentences and pattern discovery, proposed two effective approaches named as entity discovery and entity assignment
Nakayama and Fujii (2015)	Conditional Random Fields (CRF) with labels	Japanese	Hotel review	The author suggested a new approach to mine condition-sentiment associations from the text, which permits aspect-level analysis for the effectiveness of target entities depending on the customer purpose, attribute, and condition
Thet et al. (2010)	Linguistic approach, dependency syntactic tree, dictionary-based approach	English	Movie review	To find out the sentiment strength and sentiment polarity of aspects, proposed a method and adopt a linguistic approach
Lazaridou et al. (2013)	Bayesian model, LDA-style topic models	English	Hotel review	A new approach is proposed for discourse modeling. It is a simple approach that can be combined in virtually some LDA-style model of feature and opinion

Table 3 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Wang et al. (2015)	Sentiment-aspect extraction Restricted Boltzmann Machines (SERBM), LDA, Stochastic Gradient Descent (SGD)	English	Multi-domain (food, staff, ambience)	The proposed approach outperforms the baseline approach like Restricted Boltzmann Machines (RBM), RBMs with shared parameters (RSM), Loc-LDA, maximum entropy LDA, and Seeded Aspect and Sentiment model (SAS)

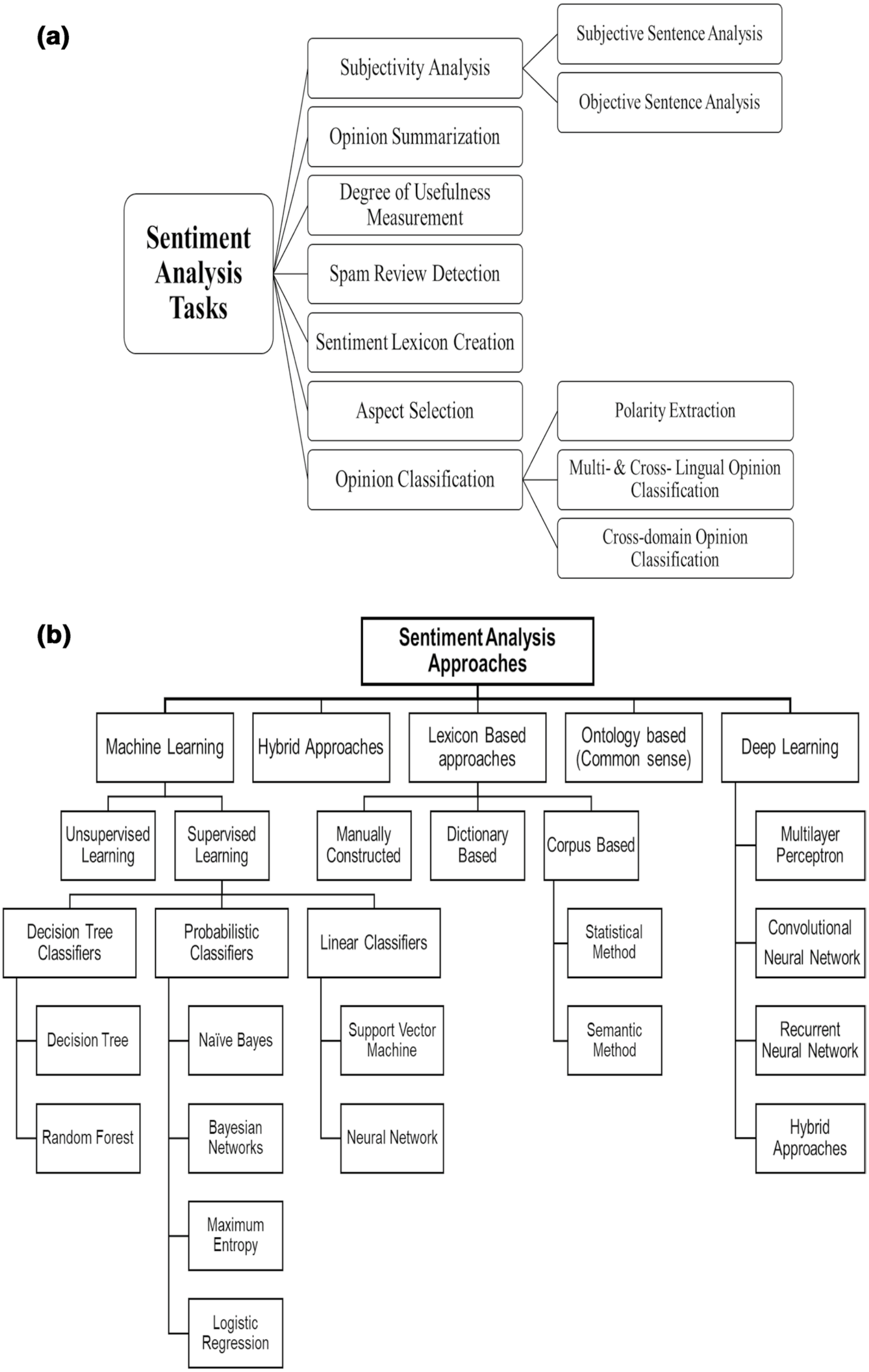

Fig. 7 Overview of sentiment analysis **a** tasks, **b** approaches

some specific approaches. This study presents the literature on sentiment analysis's tasks and applied techniques so that the new researchers can get the state-of-art in the field of sentiment analysis.

3.1 Subjectivity analysis

Subjective analysis deals with the recognition of "personal states"—a term that encompasses speculations, evaluations, opinions, emotions, sentiments, and beliefs. The sentence is divided into two dimensions objective and subjective. In an objective sentence, some factual information is available such as "*This is a university*" whereas, in the subjective sentence, some personal views, attitudes, feelings, or beliefs are available like "*This is a good university*". The expressions of subjective sentences can be considered in many forms like speculations, allegations, suspicions, desires, opinions, and beliefs. The process of analysing whether the given sentence is subjective or objective is known as Subjectivity Analysis. Subjectivity analysis is an interesting task to work upon and bridge the gap between many applications and fields. In the past decade, considerable research has been reported and improvement is still coming out from the sentence subjectivity. To obtain the subjectivity of the sentence is more complex as compared to determining the orientation of the sentence (Chaturvedi et al. 2018). The improvement in the subjectivity analysis is directly proportional to the improvement in polarity determination. Figure 8 showing the process of subjectivity analysis of the sentence. Table 4 shows the research work in the field of subjectivity analysis.

The applications of subjectivity analysis in opinion mining are feature extraction, polarity determination, and sentence sentiment mining.

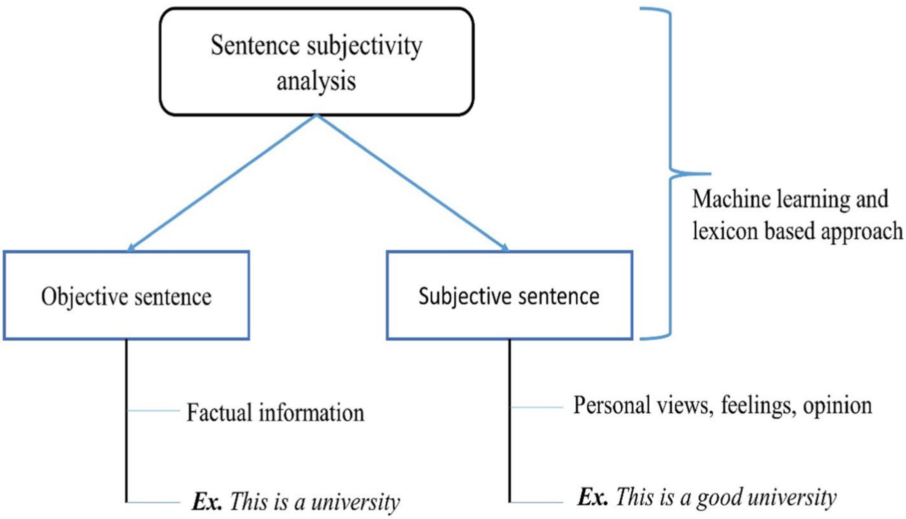

Fig. 8 Subjectivity analysis of sentence

Table 4 Compilation of research in subjectivity analysis of sentence

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Wang et al. (2011a, b)	Machine learning approach (SVM), Fisher's discriminant ratio	Chinese review	Product review (11 kinds of car)	Proposed a new feature selection technique named Fisher's discriminant ratio and compare the proposed feature selection techniques with some existing techniques such as mutual information and information gain. The authors trained SVM classifier and achieved the effectiveness of 83.3%
Banea et al. (2013)	Information gain, cross-lingual bootstrapping, SVM, multilingual bootstrapping	English and Romanian	Manually annotated data	Introduced the framework for subjectivity analysis in sense-level for multi-lingual and cross-lingual. The author considers the manually annotated data and WordNet to achieve the accuracy of 76% for both English and Romanian language
Molina-González et al. (2013)	Lexicon based approach (dictionary-based approach), Spanish opinion lexicon	Spanish	Movie review	Proposed a new resource named as Enriched Spanish opinion lexicon (eSOL) for the Spanish research community. The proposed Spanish lexicon performed well as compare to the available Spanish lexicon and achieve an accuracy of 63.16%
Bravo-marquez et al. (2014)	Lexicon based approach, SVM, Naïve Bayes, logistic, perceptron neural network	English	Micro-blogs (twitter)	Introduced a new joint approach for opinion classification for short text. The authors combined several resources and machine learning approaches for the enhancement. The experimental outcomes showing that the suggested method achieves significant improvements over any individual approach and outperformed baseline approaches

Table 4 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Pang and Lee (2004)	Naïve Bayes, SVM, minimum cuts in graphs	English	Movie review	The author applied cut-based classification for the analysis of subjectivity in the entire sentence on the document and by using per item and pairwise relationship, determine the subjective knowledge. The authors achieve an accuracy of 92% using the Naïve Bayes classifier for subjectivity classification
Xuan et al. (2012)	Maximum entropy, syntax-based patterns	English	Movie review	Utilized the syntactic information of the text and proposed syntax-based patterns for determining linguistic features. They extracted 22 syntactic information patterns based on four-part of speech including verbs, adjectives, adverbs, nouns, and some extension of the verb. To determine the subjectivity analysis, utilized maximum entropy classifier and outperforms all the baseline approaches with an accuracy of 92.1% on movie datasets

3.2 Spam review detection

With the increasing popularity of online reviews or e-commerce, the concerned person used to involve some experts in writing fake analyses of anything with the intention to increase productivity. In web 2.0, everyone is free to give their response or express their feelings from anywhere in the world without disclosing the identity. The analyses are extremely valuable for the customer. Here the concerned person may be manufacturer, dealer, service provider, political leader, market predictor, etc. Fake analyses referred to as a false review, a fraudulent review, opinion spam, fake review, etc. A spammer is a person who writes a fake review. To promote a low-quality product, a spammer used to write a false opinion for the customer. To find a fake review or opinion spam is a very tough task in the field of opinion mining. Sub-sequent part of this survey presents the process of spam review detection in Fig. 9 and research works in Table 5.

Opinion spam detection is one of the challenging tasks in the field of sentiment analysis and work is required for improvement of the accuracy and identifying the spam reviews. The applications of spam review detection in opinion mining are genuine polarity determination of product or any activity in e-commerce.

3.3 Opinion summarization

Opinion summarization can be observed as multi-document summarization (Sun et al. 2017). Opinion summarization focused on the opinion part of documents and corresponding sentiments towards the entity. Subjective information of the sentence contains opinions,

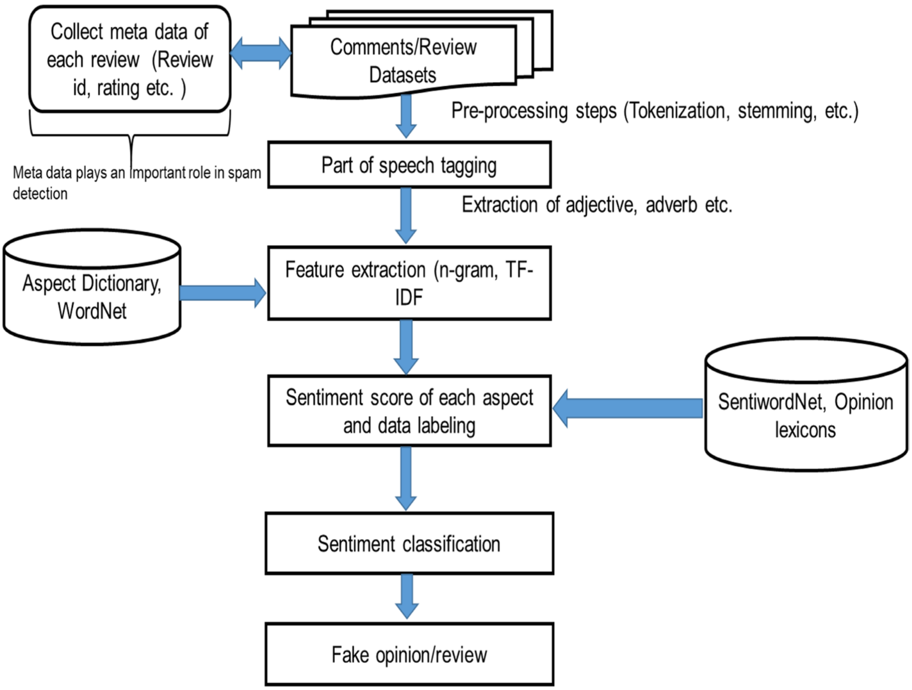

Fig. 9 Process of Spam review detection

Table 5 Compilation of research in spam review detection

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Jindal and Liu (2008)	Logistic regression, statistical package R	English	Product review (book, music, DVD/VHS, and mProducts)	This paper presented opinion spam detection based on three types of spam, like non-reviews (irrelevant reviews), detecting duplicate reviews, and reviews on brands only. The authors used logistic regression, supervised learning and manually labeling for feature extraction and opinion review identification. The experimental result showing effectiveness as a comparison to SVM and Naïve Bayes classifier
Algur et al. (2010)	Ontology-based similarity (conceptual similarity)	English	Product review (digital camera)	Proposed a new approach named as a conceptual level similarity measure for finding out the spam review or no-spam review from the product review. The experiment results showing the effectiveness of the proposed approach in categorizing and identifying the spam review, duplicate review, and non-spam review

Table 5 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Li et al. (2011)	Feature-based method, manually build a review spam corpus		Random review (labeled and unlabeled review)	Suggested a feature-based approach to determine the spam review. Based on reviews or the reviewer's opinion, they identify various features. Review related features are meta-data features, product features, sentiment features, content features, and reviewer related features are behavior feature and profile features that are further classified into some subpart. Also introduced a co-training algorithm and compare the proposed approach with different supervised and semi-supervised algorithm. The experimental results are showing improvement
Wang et al. (2011a, b)	Graph-based method, IR-based evaluation	English	www.resellerratings.com (store review data)	Proposed the new joint methods based on review graph model and iterative computational methods for detecting the spam review

Table 5 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Mukherjee et al. (2013)	Author Spamicity Model (ASM), Bayesian approach	English	Product reviews (Amazon)	Introduced a novel model for spam detection or understand the behaviour of spam review based on an unsupervised Bayesian framework. A model predicts the behaviour of spammer and nor-spammer and clusters the reviews into two different classes. The authors extracted various features like a number of reviews, the ratio of first reviews, review content similarities, reviewing bustiness', extreme rating, rating deviations, duplicate/near duplicate reviews, early time frames, and rating abuses. The experimental results showed that the proposed approach outperforms the baseline competitors
Mukherjee et al. (2012)	Frequent itemset mining (FIM), GSRank, Pattern-based method	English	Product review	Based on pattern-based method and group spammer detection techniques, identify the different features and spam reviews

Table 5 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Li et al. (2015a, b)	Average Travel Speed (ATS), Spatial Patterns, and Temporal Patterns	Chinese	Hotel reviews (Dianping)	Based on temporal and spatial patterns of spammers, proposed a novel metric to enumerate the unusual behaviors of such spammers called Average Travel Speed. The authors considered the large-scale dataset of restaurant filtered by Dianping. The dataset contains rich information like the user's IP address, user's cookies, user's profile, user's distance, weekend review, etc. Proposed approach compared with SVM and behavioural model and outperform baseline approach
Rastogi and Mehrotra (2018)	SVM, Radial-basis function (RBF)	English	YelpZip dataset	This study analyzes the textual and behavioural features in connection to both spammer detection and spam detection. They trained the SVM classifier on YelpZip labeled dataset and get comparable results for spam and spammers detection
Saeed et al. (2019)	Rule-based classifier, content-based features, Negation handling, n-gram features machine learning classifier	Arabic	Deceptive Opinion Spam Corpus (DOSC) and Hotel Arabic Reviews Dataset (HARD)	In the experiment, they considered the four different classification methods (Majority Voting Ensemble, Stacking Ensemble, Classical Machine Learning, and Rule-based) on two datasets (DOSC and HARD) in Arabic opinion texts. For feature extraction, they utilized negation handling and n-gram approach and results showing the 28% increase in the accuracy

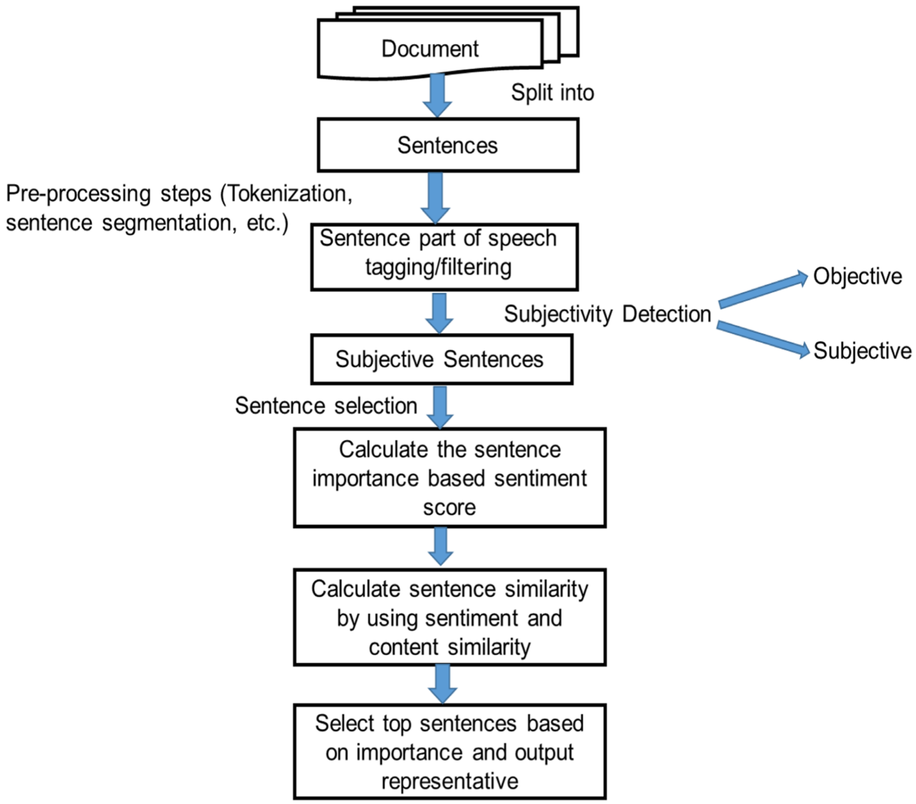

Fig. 10 Opinion summarization process

feelings, and beliefs. One opinion is not sufficient for the decision. A large number of views for a particular thing is good to analyses the opinion. In traditional text summarization, emphasized on eliminating the redundancy and mining the subjective part only. Figure 10 shows the process of opinion summarization. Table 6 summarizes research works in the area of opinion summarization.

Opinion summarization is one of the challenging area and requires attention to improve accuracy. The applications of opinion summarization are to find the overall polarity and summarize form of any documents.

3.4 Degree of usefulness measurement

The rate of reviews in e-commerce or any social issues is increasing day by day. People used to examine the reviews and based on review rating they can make their decision. To promote their services and products, some third party persons are hired by the manager for writing fake reviews. These reviews may work for some products to increase their sale. At present, spam review detection and degree of usefulness measurement gained considerable attention from the researchers. Spam detection and usefulness measurement are sub-tasks of sentiment analysis. In spam detection, only consider and analyse the good reviews because professionals write fake reviews very intelligently to increase the sale of a product or to reduce the sale of the product. The aim of usefulness measurement is to rank the reviews according to their degree which can be expressed as a regression problem with the features of review lengths, Term frequency-inverse document frequency (*TF-IDF*) weighting scores sentiment words, review rating scores, POS tags, the timeliness of reviews, reviewers' expertise's, subjectivity of reviews, review styles and social contexts of reviewers (Sun et al. 2017). The process of the degree of usefulness measurement is explained in Fig. 11. Research in the degree of usefulness measurement are explained in Table 7.

Review usefulness is one of the challenging task to work upon and still required more attention to improve the accuracy. The applications of the degree of review usefulness in opinion mining are in market prediction, box office prediction, and many more.

3.5 Sentiment lexicon creation

3.5.1 Opinion lexica and corpora creation

A vocabulary of opinion words with corresponding strength value and opinion polarity is considered as Lexicon. The creation of a lexicon is started with the primary words called opinion seed words, the list is further enhanced using antonyms, and synonyms of opinion seed words with the help of the WordNet dictionary (Ravi and Ravi 2015). This process will continue until the extension of the list does not stop. The creation of a corpus is started with the seed word of sentiment words and searches the additional sentiment words in the large corpus with context-specific orientations. In order to collect or compile the opinion words list, there are three main approaches named as manual approach or brute force approaches, corpus-based approach and dictionary-based approach. The subsequent part of this survey summarizes research work (Table 8) and process (Fig. 12) of sentiment lexicon creation.

Researchers are still working on creating general lexicon and corpus that work for all the application like in social media, e-commerce, blogs, etc.

3.6 Aspect selection

3.6.1 Feature selection for opinion classification

Feature selection is one of the most important tasks in opinion classification. Feature selection and extraction from text feature is the first step in opinion classification problem. Some of the text features like ***Negation***, ***Opinion words and phrases***, ***Part of speech (POS)***, and ***Term presence and frequency***. Feature selection methods are further divided into two sub-categories methods named as lexicon-based methods and statistical methods. In lexicon-based methods, human annotation is required and approach starts with a small set of words that are called 'seed' words. With the help of these 'seed' words, obtain the large set of lexicon through synonym and antonym. The most frequent method for feature selection is statistical methods that works automatically. The technique is used for feature selection considering the text document either as a string or a group of words (Bag of Words (BOWs)). After the pre-processing steps, feature selection plays an important role in extracting the good feature. The most frequently used

Table 6 Compilation of research in opinion summarization

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Radev et al. (2003)	Content-based similarity, co-selection, and relevance correlation	English and Chinese	People's Republic of China (LDC)	Presented an evaluation of six summarizers as well as a meta-evaluation comprising eight measures: Percent Agreement, Precision/Recall, Relevance Correlation, Kappa, Relative Utility, and Content-Based measures (longest common subsequence, cosine, and word overlap)
Carenini et al. (2006)	Summarizer of Evaluative Arguments (SEA), MEAD*	English	Product reviews (digital camera)	The experimental results are showing the comparison of SEA, MEAD*, Document Understanding Conference (DUC) and the human summarizer. The proposed approach got comparable results with a human summarizer
Lerman et al. (2009)	Ranking SVM model, Sentiment-Aspect Match Model (SAM), SMAC	English	Product review (Digital cameras, MP3 players, wireless routers, printers, and video game)	The experimental results are showing that the ranking SVM performs well in comparison with SAM, SMAC, and SM
Nishikawa et al. (2010)	Integer Linear Programming (ILP), content score, coherence score, passive-aggressive algorithm	English	Reviews of commodities (digital cameras, printers, video games, and wines) and restaurants, Graph-based approach	Proposed a new method for opinion summarization based on content and coherent score simultaneously. A novel approach is based on the graph. Document sentences are represented as a node in the graph. The experiment results are showing that the proposed approach performs well as comparison with (Lerman et al. 2009) and (Carenini et al. 2006)

Table 6 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Gerani et al. (2014)	Page Rank algorithm, template-based natural language generation (NLG) framework, Graph-based model	English	Product review (Antivirus, diaper, digital camera, router, MP3 player, DVD player, and phone)	Suggested a novel framework based on discourse structure for abstractive summarization of reviews. Proposed graph-based model and, natural language generation (NLG) framework for content selection and abstract generation (to generate the abstractive summary). The experimental results compare with the existing approach (MEAD-LexRank (LR), MEADStar (MEAD*) and simple abstractive and found that the proposed approach outperformed the state-of-art
Hu et al. (2017)	k -medoids clustering algorithm, content and sentiment similarities, NGD and point-wise mutual information	English	Hotel review	Introduced a new approach for opinion summarization on hotel review based on k -medoids clustering algorithm. The proposed framework is divided into sub-categories like Review pre-processing, sentence similarity calculation, sentence importance calculation, and top-k sentence selection. These sub-categories are further divided into sub-tasks. This study has some limitations

Table 6 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Chakraborty et al. (2019)	Graph-based approach (tweet similarity graph (TSG)), minimum dominating set (MDS)-approach	English	New articles (political news from New York Post, Twitter Data Set (36 million unique users and 77 million hashtags)	The proposed graph-based approach (tweet similarity graph (TSG)) is proposed to identify the diverse opinions from the tweets and analyze the communities of tweets. After that select the tweets from the communities by using minimum dominating set (MDS)-approach. The proposed approach performs well for news tweet summarization
Wu et al. (2019a, b)	Ortony-Clore-Collins (OCC) model, Convolutional Neural Network, Word2Vec methodology	Chinese	Sina Microblog (Tianjin explosion accident, arson case committed by housekeeping in Hangzhou, Terminal High Altitude Area defense (THAAF)	Introduced Ortony-Clore-Collins (OCC) rule library for sentiment classification and utilized a convolutional neural network for opinion summarization on Chinese microblogging systems. The experiment results are comparable in real-world microblog data

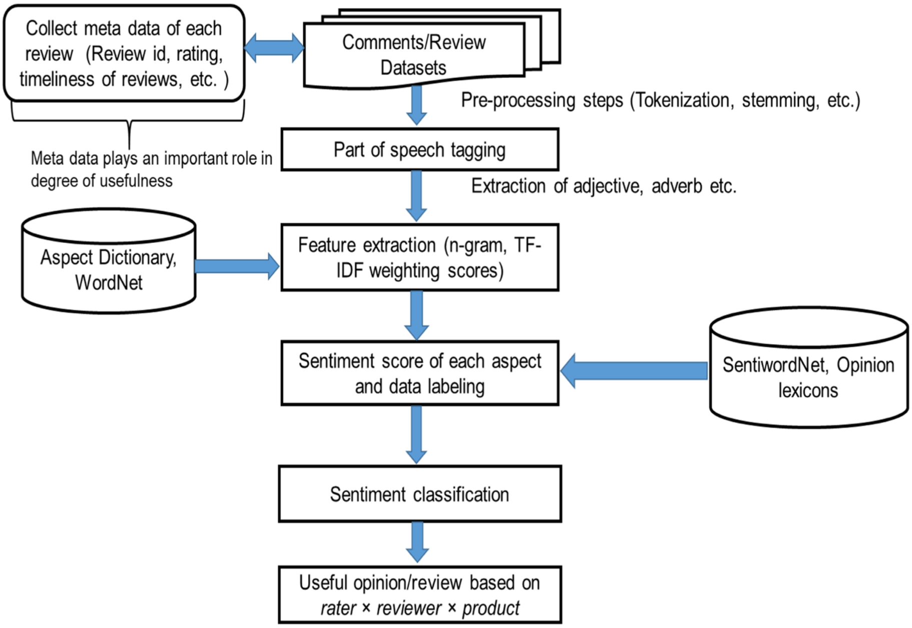

Fig. 11 Process of Degree of usefulness measurement

statistical methods for feature selection are Chi square (χ^2), *Point-wise Mutual Information* (*PMI*), Principal Component Analysis techniques (*PCA*), Hidden Markov Model (*HMM*), Latent Dirichlet Allocation (*LDA*), etc. Figure 13 explains the process of aspect selection. Table 9 summarizes existing research work in aspect selection for opinion classification.

There are some challenging tasks in feature detection such as irony detection, sparsity, polysemy detection, etc. that required more attention.

3.7 Opinion classification

The main objective of opinion classification is to determine the sentiment orientation of the given text. The sentiment orientation of given text is to find the polarity of a given text, whether the given text expresses the positive, negative or neutral opinion towards the subject. The classes of polarity can be varied like a binary (positive or negative), ternary (positive, negative, or neutral) and n-ary. In order to achieve the objective, many techniques are available named as machine learning, lexicon-based and hybrid techniques. The Machine Learning technique applies the well-known machine learning algorithms and uses linguistic features. For classifying the text, it observed that machine-learning techniques are divided into unsupervised and supervised learning methods. In supervised learning approaches, a large amount of labeled training data is available. Whereas in unsupervised learning approaches, it is difficult to find the labeled training data. Some frequently used machine learning methods are Support vector machine, Naïve Bayes, Maximum Entropy, Decision Tree, Neural Network, Bayesian Network, and Rule-based classifier. The *Lexicon-based* approach depends

Table 7 Compilation of research in degree of usefulness measurement

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Moghaddam et al. (2012)	Collaborative Filtering (CF), Matrix Factorization and Extended Tensor Factorization, unBiased Extended tensor factorization (BETF)	English	Product review (books, movies, laptops, software digital cameras)	To predict the quality review, they proposed probabilistic factorization models such as Matrix Factorization, Tensor Factorization, Extended Tensor Factorization, and unBiased ETF. The factorization is performed based on rater × reviewer × product. The experimental results are shown that the proposed models perform well as compare to the regression approach like linear regression, SVM, collaborative filtering. This article suggests many future directions for measuring the usefulness of the review
Purnawirawan et al. (2012)	Lexicon based approach (dictionary-based approach), perceived usefulness, review impression	English	Product reviews	The objective of this paper is to study the impact of sequence (reviews order) and balanced (the ratio of negative and positive review) reviews on the perceived usefulness of these reviews and measure the usefulness of reviews. From the investigation, they found that balanced reviews either positive or negative having a good impact as compare to neutral review and review sequence also have the important effort measure the usefulness by wrapping polarity-based review into another. The experiments are performed on 8–8 reviews (positive and negative reviews) on 4 review sequences (positive/negative/positive, positive/negative, negative/positive/negative, negative/positive) and 3 reviews balanced review (negative, neutral, positive)

Table 7 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Huang and Yen (2013)	Linear Regression (regression equation)	English	Product reviews (printer, video game, camera, printer, iPod	To measure the helpfulness of product reviews, they introduced two modified regression equations. The experiments are performed on the same type of product but some new version
Lee and Choeh (2014)	Helpfulness prediction model using a neural network (HPNN), Back-propagation multilayer perceptron neural networks (BPN)	English	Product review (baby product, DVD, kitchen, music, Video, etc.)	The main objective of this paper is to determine the usefulness of review with the help of some tools. They proposed one model named helpfulness prediction model using a neural network based on Back-propagation multilayer perceptron neural networks to predict the review helpfulness, textual characteristic of reviews and review characteristics. The proposed model performed well as compared to linear regression analysis based on mean-squared error
Ngo-Ye and Sinha (2014)	Recency, Frequency, Monetary (RFM) Analysis, bag-of-words, Weka's SVR implementation, and BOW′+RFM model, vector space model	English	Product review (book from Amazon, a restaurant from Yelp)	For predicting the usefulness of reviews, they proposed and compared various text regression models. They observe the impact of reviewer engagement features like current activity, commitment, and reputation along with review word as a predictor. They employed the vector space model, (Recency, Frequency, and Monetary Value) RFM score and bag-of-words to predict the helpfulness using the SVR Model. The experiment results are comparable with previous approaches

Table 7 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Min and Park (2012)	Metric based approach and Reviewer Information based on experience and rule base classifier	English	Product reviews (apparel and beauty)	To recognize the high eminence reviews, they introduced a novel metric to rank the reviews based on experiences. They emphasized the reviews written by experiences reviewers as compare to the professional reviewer. To measure the usefulness, they concentrate on used product duration (time tagger and TERN evaluation), count of same brand product used earlier, and details about product use. The experiments are performed for two product reviews (apparel and beauty) and reported f-measure and accuracy as 88.58% and 83.33% respectively. RBC gives comparable results with decision tree and SVM

Table 7 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Krishnamoorthy (2015)	SVM, Naive Bayes (NB), Linguistic Category Model, SentiWordNet, Random Forest (RandF)	English	Product review (books, music, and video games)	To calculate the usefulness of review, they considered some features like subjectivity features, linguistic features (such as action verbs, state verbs, and adjectives), readability and review metadata. Based on this feature they introduced a predictive model to measure the usefulness. The experiment is performed on different products review and get the f-measure of 87.21% and 81.33% correspondingly using Random Forest (RandF). The proposed predictive model performs well as compared to NB and SVM. Linguistic feature performs well as compared with another type of features
Liu et al. (2013a, b)	Bootstrapping, simple linear regression (SLR), Decision tree (DT), principal component analysis (PCA), Sequential minimal optimization, Simple linear regression (SMO-SVM) or SMOreg, multilayer perception neural network	English	Product reviews (Mobile phone)	To measure the degree helpfulness of review, they proposed an approach in two phases. In the first phase, the feature is extracted using a Point-wise mutual information-based document profile model and for measuring the usefulness, they used the decision tree along with the bootstrap approach. It performed well as compare to simple linear regression, multilayer perceptron, and SMOreg. In the second phase of the approach, for measuring the helpfulness, they applied some feature selection approaches like mutual information, feature-instance similarity and principal component analysis

Table 7 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Lubis et al. (2017)	Naive Bayes algorithm, data filtering, and Laplace smoothing	English	Massive Open Online Course (MOOC) (class-central.com)	Utilized the Naive Bayes algorithm to categorize helpful reviews automatically on the course review dataset
Lee et al. (2018)	SVM, logistic regression, decision tree, random forest	English	TripAdvisor.com (1,170,246 hotel reviews)	Developed a review helpfulness prediction model by using the different classification techniques and shows that the random forest performs better than the Support vector machine, logistic regression, and decision tree

Table 8 Compilation of research in sentiment lexicon creation

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Patodkar and Sheikh (2016)	Tree Tagger, n-gram as a binary feature, multinomial Naive Bayes classifier, SVM, CRF	English	Microblog review (Twitter account of popular newspapers and magazines)	Proposed a new approach for automatic collection of a corpus-based on a multinomial NB classifier using POS-tags and n-gram as features. To determine the difference in distributions among negative, neutral and positive sets and POS-tagging, Tree Tagger method used. The experiment results show that the suggested techniques perform better than the existing techniques
Qiu et al. (2010)	Rule-Based, Dissatisfaction oriented Advertising based on Sentiment Analysis (DASA)	English	Web Forums (automotvieforums.com)	To classify subjective sentences in contextual advertising, they used a dictionary-based approach. To increase user experience and ad relevance, proposed an advertising strategy. The author used the proposed rule-based approach, sentiment dictionary, and syntactic parsing to determine topic words and customer attitudes. The experimental results are showing the usefulness of the suggested method on ad selection and advertising keyword extraction
Tsai et al. (2013)	Iterative regression, Random walk method, support vector regression, In-link normalization, and Out link normalization	English	Affective Norms for English Words (ANEW), ConceptNet	In order to construct a sentiment dictionary based on ConceptNet, the iterative regression model is used. The regression framework was built upon polarity and concept sentiment value, concept, and features of neighboring concepts. A support vector machine was used for the regression framework that was trained on ANEW and SenticNet dataset and tested on another dataset

Table 8 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Baccianella et al. (2008)	Random-walk method	English		To determine the sentiment score of opinion words, SentiWordNet 3.0 is the most favorable lexical resource. The three types of sentiment scores (Pos., Neg., Obj.) are defined and range from 0.0 to 1.0 for each verb, adverb, adjective, and noun, as in WordNet
Poria et al. (2013)	Fuzzy clustering, Point-wise mutual information, lexicon-based approach, dictionary-based approach	English	WordNet (WN), International Survey of Emotion Antecedents and Reactions (ISEAR) dataset, WordNet-Affect, and SenticNet	The authors extend the SenticNet 1.0 with the emotion level consider from WordNet-Affect. To assign the WordNet-Affect sentiment labels to SenticNet's concepts used supervised machine learning. International Survey of Emotion Antecedents and Reactions (ISEAR) dataset are used to extract the feature and these features considered for the classification. The support vector classifier performs better than Naïve biased and MLP and achieves an accuracy of 88.64%
Maks and Vossen (2012)	Lexicon Based Approach, Dictionary-based approach	Dutch	Dutch WordNet, Global Domain	This article extends the existing Dutch lexicon and considered subjectivity such as character subjectivity, epistemic subjectivity, and speaker subjectivity

Table 8 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Cambria et al. (2015)	Extreme learning machine (ELM), k-NN, k-medoids, discrete' neural network, continuous' neural network and principal component analysis (PCA)	English	Global Data, ConceptNet, WordNet-Affect, 100-dimensional Affective Space	The objective of this paper is to make high generalization performance, fast learning (easy adaptation) and low computational complexity that can be exploited to execute analogical reasoning in a vector space model of affective common-sense knowledge. To capture multi-word expressions, suggested a new cognitive model using ConceptNet and WordNet-Affect. PCA, k-NN, and k-medoids were applied for feature selection and to figure out semantically related concepts respectively. Continuous neural network (CNN) and discrete neural network (DNN) was applied to find out the level of affective valence
Velikovich et al. (2010)	Graph propagation algorithms	English	Global data, WordNet	The authors build the English lexicon that is larger than the previous existing lexicon
Trainor et al. (2013)	Confirmatory factor analysis (CFA) model, Customer relationship management (CRM), and structural equation modeling (SEM)	English	Survey data from industries (U.S. organization), ConceptNet	The impact of this study is conceptualization and dimension of social Customer relationship management capability and figure out how Customer relationship management capability is influenced by social media technologies and customer-centric management systems. To analyze the Survey data that is collected from industries (U.S. organization), they used a structural equation modeling approach

Table 8 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Nielsen (2011)	Lexicon Based approach (dictionary-based approach)	English	Affective Norms for English Words (ANEW), Micro Blogs	Presented an extended version of the existing opinion lexicon AFINN-96. Lexica and corpora comprise tweets on the United nation Climate Conference, Wiktionary, Urban dictionary, Original Balanced Affective Word List, the Compass DeRose Guide to Emotion Words, etc. The proposed extended version of the lexicon performs well in comparison with Affective Norms for English Words but not SentiStrength for Twitter data
Cambria et al. (2012)	Lexicon Based approach, concept frequency-inverse opinion frequency, multi-dimensional vector space, and Affective Space	English	WordNet-Affect (WNA), ConceptNet	Based on sentic computing and the concept of social and computer science, they proposed SenticNet 2.0. To bridge the semantics and sentics (cognitive and affective) gap between concept-level sentiments and word-level natural language data, developed a publicly available resource for sentiment analysis, social data mining, social media marketing, and multimodal affective HCI
Cambria et al. (2018)	Bi-Long short-term memory (biLSTM), word embedding, recurrent neural networks	English	2-billion-word ukWaC, Blitzer Dataset	To detect the conceptual primitives for opinion mining, they utilized an ensemble of symbolic and subsymbolic AI

Table 8 (continued)

References	Approaches/techniques	Dataset language	Dataset/corpora	Details
Wu et al. (2019a, b)	One class SVM, Syntactic information, word2vec	English	Kitchen, apparel electronics and sports	This study aims to create a target-specific sentiment lexicon. The authors' utilized unsupervised algorithms along with semantic and syntactic features, to extract the target-specific opinion lexicon

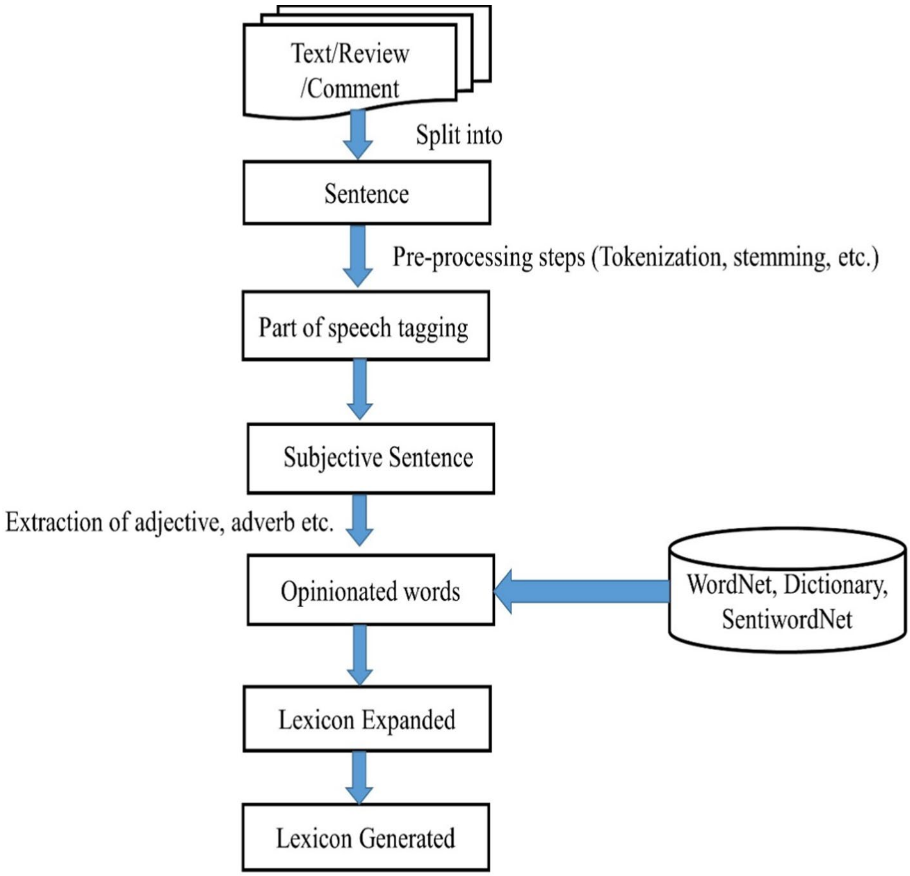

Fig. 12 Process of sentiment lexicon creation

on an opinion lexicon that is a group of recognized and precompiled opinion terms. To analyse the text, lexicon-based techniques are used to find the sentiment lexicon. There are two approaches in this technique named as *dictionary-based approach* and a *corpus-based approach*. The *dictionary-based approach* is based on *seed* words and according to *seed* words, find out their synonyms and antonyms in the dictionary. *The corpus-based approach*, which uses *statistical* or *semantic* methods to find the other sentiment words in a huge corpus with context-specific orientations that begin with a seed list of sentiment words. The hybrid technique combines both Machine-learning and Lexicon-based approach with the objective to find the polarity of the text (sentences, documents, etc.) towards the subject. The objective of the opinion classification is to determine the polarity in multiple fields like multi-lingual, cross-lingual, and cross-domain, etc. The process of opinion classification is explained in Fig. 14. The current state of art, techniques, common datasets that are used for polarity determination explained in Table 10.

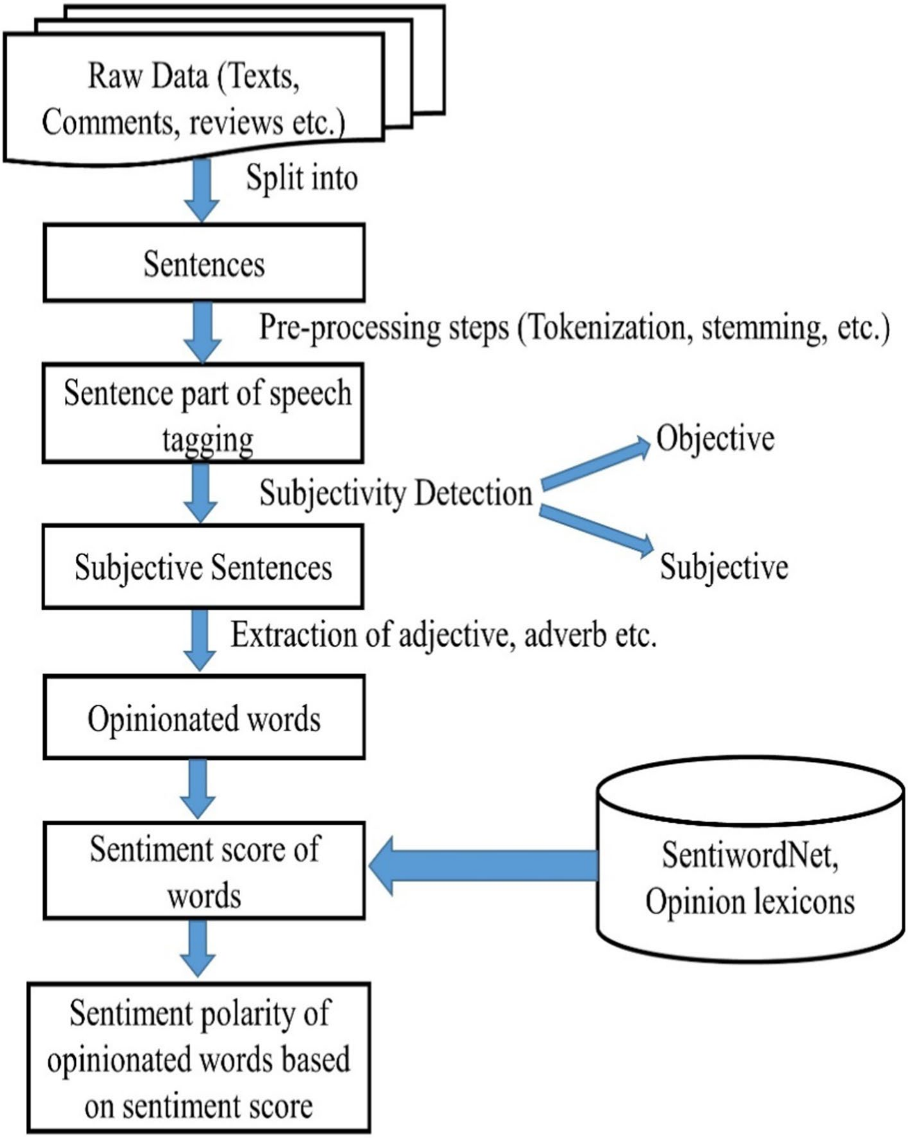

Fig. 13 Process of aspect selection

Researchers are still working to determine the polarity of texts, documents, and sentences by using a machine-learning approach, lexicon-based approach and hybrid approach along with feature extraction techniques. The challenging task of polarity determination is to yield good accuracy.

Table 9 Compilation of research in aspect selection

References	Approaches/techniques	Data language	Dataset/corpora	Details
Yu et al. (2013a, b)	Pointwise Mutual Information Based (PMI)	English	Stock news	The author extended the existing basic PMI method by introducing the new method named as contextual entropy model. To measure the similarity between two words using entropy models and expand the set of seed words, they employed the Contextual entropy model. This method outperformed basic *PMI*
Fan and Chang (2011)	Chi square, SVM	English	Buyers' posts web pages (epinions.com, wikipedia.com ebay.com)	To increase online contextual advertising, introduced bloggers' immediate personal interests. They consider the data from different sources like Wikipedia.com, ebay.com, and epinions.com on blog pages and ads. They used feature selection techniques named as Chi square and classification methods support vector machine. The experimental results showed that the suggested approach successfully classify positively correlated ads with a blogger's interests
Duric and Song (2012)	ME, Statistical approach (Hidden Markov Model—Latent Dirichlet Allocation (HMM—LDA))	English	Movie reviews	To extract the feature and separate the entities in review documents, they used statistical approaches like Hidden Markov Model and Latent Dirichlet Allocation. For feature selection using the topic model approach HMM-LDA and for polarity determination, utilized Maximum entropy classifier on movie reviews

Table 9 (continued)

References	Approaches/techniques	Data language	Dataset/corpora	Details
Rabelo et al. (2012)	Link mining, Collective classification	English	Microblogs (Social Networking Twitter data)	Utilized a user-centric approach and link mining with the aim to get the sentiment expressed by the user. For applying the collective classification algorithm, the author selected an 800-hashtag post and get 97,000 nodes and approximately 1 million edges for the graph. The experiments showed promising results
Sobkowicz et al. (2012)	Markov-Chain Monte Carlo (MCMC)	English	Online discussion	Suggested a framework that is based on sociophysical system modeling and content analysis of social media with the objective to get the opinion formation form affordable and ubiquitous social media communications
García-moya et al. (2013)	n-gram, language modeling, Expectation–maximization (EM), lexicon-based approach	English and Spanish	Product review (digital cameras, phones, routers), Taxonomy-Based Opinion Dataset (TBOD) (cars, headphones, and hotels)	Proposed a framework for feature summarization of review named as language modeling. The proposed framework combines a stochastic mapping between words and a probabilistic model of opinion words. To minimize the cross-entropy utilized Expectation–Maximization and to learn the model of seed words, used a kernel-based density estimation method. The proposed approach outperformed the baseline method named Hyperlink-Induced Topic Search and Double Propagation

Table 9 (continued)

References	Approaches/techniques	Data language	Dataset/corpora	Details
Jung (2012)	Maximum Entropy, Contextual association	English	Microblogs (social networking micro text twitter)	In order to recognize the entities, utilized the Named entity recognition methods based on maximum entropy. The experimental results are showing that the proposed approach performs well for extracting the relevant information
Quan and Ren (2014)	General Inquirer—Support vector machine (with the polynomial kernel). Lexicon based approach, PMI–TFIDF	English	Product review (digital cameras, phones, routers), General Inquirer	To recognize the relationship between domain entities and their features, introduced a novel similarity measure named PMI-TFIDF. Compared with PMI, PMI-TFIDF perform well and shows better results
Zhang et al. (2014)	Syntactic semantic features and Conditional random fields	English	Comments on Facebook pages, online customer reviews (digital camera, TV) Amazon	To extract the features from the datasets, they incorporated conditional random fields with semantic and syntactic features such as comparative and superlative POS, positive and negative emotions, conjunction terms, similarity to neighboring sentences, word positions, etc. For opinion classification, proposed a context-based method and experiment performed on different datasets like 500 facebook reviews, 300 digital reviews, and 300 TV reviews. The proposed method outperformed support vector machine, Logistic Regression, Hidden Markov Model and rule-based algorithm (Compositional Semantic Rule)

Table 9 (continued)

References	Approaches/techniques	Data language	Dataset/corpora	Details
Zheng et al. (2014)	Latent Dirichlet Allocation, Appraisal expression pattern	English	Product review (cameras, MP3), hotel review, restaurant review	To extract the features and opinions, they incorporated Latent Dirichlet Allocation with an appraisal expression pattern (APE-LDA). With the shortest dependency path between the part of speech, they captured the appraisal expression pattern. The proposed approach outperforms pointwise mutual information and nearest neighbor technique for opinion word recognition
Xu et al. (2015)	Latent Dirichlet Allocation, SVM, PMI	Chinese	Product review (cell phone)	To extract the implicit features, they proposed a model that uses the concept of Latent Dirichlet allocation and SVM. Latent Dirichlet allocation is used to extract the explicit feature and experiments are performed in 14,218 Chinese sentences on a cell phone from 360buy.com and get the f-measure of 77.78%
Yan et al. (2015)	Lexicon creation (synonym expansion), Extended PageRank algorithm	Chinese	Product review (digital camera, mobile phone, and DVD player)	To extract the features and dependency relation between associated opinion words and noun phrases, introduced a method name as EXPRS (an Extended PageRank algorithm enhanced by a Synonym lexicon). The experiments are performed on product reviews (11,291Canon EOS 600D, 8901 Samsung GalaxyNote II, and 9000 Philips DVP3600) and get the f-measure of 76.2%, 73.0%, and 72.7% on respective product reviews

Table 9 (continued)

References	Approaches/techniques	Data language	Dataset/corpora	Details
Li et al. (2015b)	PMI-IR, RCut, Apriori Algorithm (frequency-based mining and pruning, similarity-based filtering and order-based filtering)	Chinese	Product review (g mobile phone, digital camera, MP3 player, and LED monitor) (http://www.it168.com)	In order to extract the product features from reviews, they proposed a method that consists of three components. The first component performed frequency-based mining and pruning, the second component performed order-based filtering and the third component performed similarity-based filtering. Similarity-based filtering further divided into two components, in the first step, the author measured the semantic association between the corresponding product entity and frequent aspects. In the second step, for selecting the set of aspects they used a threshold-learning method named RCut. The experiment result performed an average f-score of 73.3%
Wang et al. (2014)	LDA incorporated with domain knowledge, cosine similarity, RandIndex, Entropy, and Purity	English	Product review (camera)	To extract the feature for reviews, they incorporated two semi-supervised models. The first model named Fine-grained Labeled LDA (FL-LDA) was incorporated with seeding aspects. The second model named Unified Fine-grained Labeled LDA (UFL-LDA) incorporated with unlabeled high-frequency words. In the experiment, they used cosine similarity RandIndex, Entropy, and Purity for aspect hierarchies

Table 9 (continued)

References	Approaches/techniques	Data language	Dataset/corpora	Details
Xueke et al. (2013)	Latent Dirichlet Allocation (LDA), Lexicon based approach, MPQA, SentiWordNet, SVM with linear kernel	English	Restaurant reviews, hotel review	To mining the features, they developed a method named as Joint Aspect/Sentiment model (JAS) and feature dependent opinion lexicons. The author utilized SentiWordNet, MPQA, and union of them as sentiment lexicon. The experiments are executed on hotel reviews and restaurant reviews and the proposed model outperformed some models like Aspect and Sentiment Unification Model (ASUM) and MaxEnt-LDA

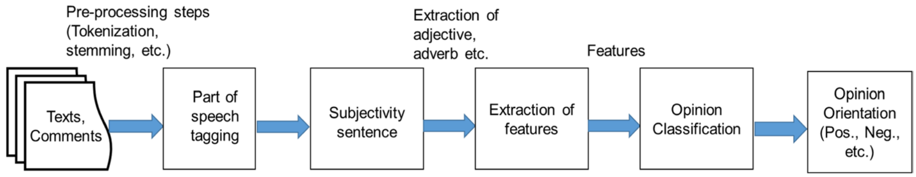

Fig. 14 Process of Opinion classification

3.7.1 Cross-lingual and multi-lingual opinion classification

To determine the opinion, annotated corpora and sentiment lexicons i.e., sentiment resources are very crucial. However, most of the existing resources are written in the English language. To concern the opinions, the numbers of languages are available across the world with different degrees of sensitive power that makes it complex to achieve precise analysis for texts in different languages such as Spanish, Arabic, and Japanese, etc. It is very expensive to create sentiment lexicon or sentiment corpora for every language (Dashtipour et al. 2016). In cross-lingual opinion mining, the machine is trained on a dataset of one language (source language, which is having reliable resource e.g. English) and tested on a dataset of another language (target language or resource lacking language) whereas, in multi-lingual opinion analysis, mixed language is present (Singh and Sachan 2019). Using two different approaches, cross-lingual and multi-lingual opinion analysis can be performed e.g. lexicon-based approach and corpus-based approach. The Generalized process of multi-lingual opinion classification is described in Fig. 15. The current state of art, techniques, common datasets that are used for Cross-lingual and multi-lingual opinion analysis explained in Table 11.

Cross-lingual and multi-lingual sentiment analysis requires more attention in different aspects like code-mixed, phonetic words, social media code mixed, social media content etc. (Lo et al. 2017).

3.7.2 Cross-domain opinion classification

In the field of sentiment analysis, cross-domain sentiment analysis is one of the challenging and interesting problems to work upon. The opinion is expressed differently in a different domain that means a word is expressed positive sentiment towards a domain and the same word expressed negative sentiment towards another domain ("*A Domain is a class that consists of different objects*"). For example, if we considered two domains like "Hotel" and "computer" and a word like "Hot" will explain the challenging task of cross-domain sentiment analysis. In the case of the computer domain "The computer is too hot when it working" word "hot" express negative sentiment. When we are referring the case of the hotel domain like "The shower is having the great hot water" now the word "hot" expresses the positive sentiment. Due to this, the performance of the trained system will drop drastically. We can't create the corpus for all the domains. Creating a corpus for all the domains is a very time consuming and costly process. Cross-domain sentiment analysis requires at least two domains, one is called a source domain and the other is called is a target domain. We get the training set from the source and target domain and train our classifier based on this training set. Once our classifier is trained, it is tested on the target domain and its accuracy is checked.

Table 10 Compilation of research in opinion classification

References	Approaches/techniques	Dataset/corpora	Data scope	Details
Saleh et al. (2011)	Support vector machine	Pang and Lee (2004) v2.0 dataset, Taboada and Grieve (2004) SINAI corpus of digital cameras, multi-domain corpora	Product review (digital camera), movie review	(a) Using Pang and Lee dataset, binary and tri-gram occurrences achieve accuracy of 85. 35% (b) Using Taboada and Grieve multi-domain corpora, term frequency-inverse document frequency and trigram achieve accuracy of 73. 25% (c) Using SINAI corpus term frequency-inverse document frequency and bigram achieves the accuracy of 73. 25%
Pang et al. (2002)	Support vector machine, Naïve Bayes, Maximum Entropy	Pang et al. (2002) v1.0, English	Movie review (IMDb.com)	(a) SVM using unigram achieve an accuracy of 82.9% (b) NB using unigram achieve accuracy of 78.7% (c) ME using adjectives achieve accuracy 77.7%
Bai (2011)	Markov Blanket Classifier, Tabu search (TS), and Bayesian network, Markov Blanket Directed Acyclic Graph (MB-DAG)	Pang et al. (2002) v1.0, Pang and Lee (2004) v2.0, English	Movie review, online new review by Infonic Ltd (Financial, Mixed, and mergers and acquisitions)	(a) Tabu search Markov Blanket Classifier (TS-MBC) used a combination of unigrams and semantic features on Pang and Lee v2.0 data set achieved accuracy 92.70% (b) Tabu search Markov Blanket Classifier (TS-MBC) used a combination of unigrams and semantic features on Pang and Lee v1.0 data set achieved accuracy 78.08%

Table 10 (continued)

References	Approaches/techniques	Dataset/corpora	Data scope	Details
Dang et al. (2010)	Support vector machine, Feature extraction using SVM (Content free, content-specific) and semantic orientation (semantic feature), Information gain	Blitzer et al. datasets (multi-domain set), English	Product review (books, DVD's, kitchen appliances, electronics)	Using SVM and different feature extraction methods, classified the opinion and achieve an accuracy of 84.15% for kitchen appliances
Zhang et al. (2011)	Support vector machine, n-gram, unigram_freq, bigram_freq, trigram_freq, and varying number, Naïve Bayes	Cantonese (variety of Chinese spoken)	Restaurant review	Utilized different machine-learning (SVM and NB) and feature representations techniques for restaurant reviews and classified the opinion based on these approaches and achieve an accuracy of 95.76% using the NB classifier for 900-1100 features
Deng et al. (2014)	Lexicon based approach, SVM classifier, Statistical feature selection methods (Weighed Frequency and Odds (*WFO*), Weighted Log-Likelihood Ratio (*WLLR*), Chi square statistic ($\chi 2$), mutual information, information gain (*IG*), document frequency (*DF*) and odds ratio (*OR*)	(Pang et al. 2002) v1.0 and Blitzer et al. datasets (multi-domain set), Maas et al. English	Movie reviews and Product review (books, DVD's, kitchen appliances, and electronics) (Amazon.com), Stanford large movie reviews	The experiment performed (a) On Pang and Lee v1.0 dataset, using SVM classifier and proposed weighting schemes achieve an accuracy of 88.5% (b) On Blitzer et al. dataset (multi-domain dataset), using SVM classifier and proposed weighting schemes achieve an accuracy of 88.7% (c) On Maas et al. dataset, using SVM classifier and proposed weighting schemes achieve an accuracy of 88.0%

Table 10 (continued)

References	Approaches/techniques	Dataset/corpora	Data scope	Details
Whitelaw et al. (2005)	Lexicon based approach, SVM, SMO-SVM, Feature sets of appraisal groups (Words by Attitude, Systems by Attitude, Systems by Attitude and Orientation, Appraisal Group by Attitude, Appraisal Group by Attitude and Orientation, Orientation, and Force, and Bag of Words)	Pang and Lee (2004) v2.0, English	Movie review	An experiment performed on Pang and Lee v2.0 dataset, using a support vector machine classifier with the union of Bag of Words and Appraisal Group by Attitude and Orientation feature selection methods that achieve an accuracy of 90.2%
Mullen and Collier (2004)	SVM, Osgoodian values, PMI-IR method	Pang and Lee v1.0 English	Movie review and media reviews	The experiments are executed on Pang and Lee v1.0 movie dataset and 100 media reviews. By using a support vector machine along with PMI-IR/Osgoodian semantic feature selection technique, achieved an accuracy of 87%
Agarwal et al. (2011)	Lexicon based approach, Support vector machine, unigram model, feature-based model (Semi-feature model) and tree kernel-based model	English (11,875 manually annotated Twitter)	Microblogs (Twitter data)	Two-way classification, support vector machine along with semi-features performed better than other combinations of model and yield accuracy of 75.39%. Whereas for 3-way classification, semi-features along with the tree kernel model outperformed other feature models and yield an accuracy of 60.83%

Table 10 (continued)

References	Approaches/techniques	Dataset/corpora	Data scope	Details
Abbasi et al. (2011)	Rule-based multivariate features, SVM, feature relation Network (FRN), lexical resources, n-gram	Pang and Lee v1.0, epinions.com, edmunds.com, English	Movie review, Product review (digital camera 2000 reviews), Automobile (2000 reviews)	The experiment performed on Pang and Lee v2.0 dataset, digital camera review and automobile dataset, with feature relation network (FRN) (n-gram feature selection method, multi-variate, rule-based) method yield the accuracy of approximately 90% and suggested technique outperformed Chi square, log-likelihood ratio (LL), bag of words/LL and word n-grams/LL
Prabowo and Thelwall (2009)	Lexicon based approach (SentiWordNet), Support vector machine, General Inquirer based classifier (GIBC), induction rule-based classifier (IRBC) (like ID3 and Ripper) and statistics based classifier, the rule-based classifier	Pang and Lee v2.0, MySpace comments	Movie review (100 +ve and 100 –ve reviews, Product review (180 +ve and 180 –ve reviews), Restaurant Review (110 +ve and 110-ve reviews)	The experiments are executed on Pang and Lee v1.0 dataset, Myspace comments (restaurant review) and product reviews by using different hybrid classifier over five classifier Support vector machine, General Inquirer based classifier (GIBC), statistics based classifier, induction rule-based classifier (like ID3 and Ripper) and rule-based classifier with F1 measure of 90.45% on Myspace comments
Abdul-mageed et al. (2013)	SVM^{light}, subjectivity and sentiment analysis (SSA)	3015 Arabic tweets, 2798 chat turns, 3008 sentences from 3097 web forum sentences and Arabic Wikipedia talk pages	Dialects, microblogs, Wiki Talks,	The experiments are performed on different data sets by using SVM^{light}, Subjectivity and sentiment analysis and yield the accuracy of 84.36% for a web forum, and 70.30% for chat turns

Table 10 (continued)

References	Approaches/techniques	Dataset/corpora	Data scope	Details
Xia et al. (2011)	Naïve Bayes, Maximum Entropy, SVM, world-relation based feature sets and POS-based features	Pang and Lee (2004) v2.0, Blitzer et al. (2007), English	Movie review, product review (book's, DVD's, kitchen appliances, electronics)	The experiments are performed on two different datasets, by using features sets (world-relation and part of speech feature), classifiers and 3 different techniques (meta-classifier combination, weighted combination and fixed combination) with the accuracy of 87.7% and 85.15%
Ortigosa et al. (2013)	Hybrid approach (Lexicon based and machine learning approach), SVM, Naïve Bayes, J48 (C4.5 decision tree), Spanish Linguistic Inquiry and Word Count (LIWC)	Spanish (Word Count and Linguistic Inquiry)	Facebook comments (3000 status messages) for the three different class viz. positive, negative and neutral	Proposed a lexicon and evaluate with SVM, Naïve Bayes, and J48 (C4.5 decision tree) and achieved an accuracy of 83.27%, 83.13%, and 83.17% respectively
Poria et al. (2016a, b)	Deep Convolutional Neural Networks, Word Embeddings (word2vec vectors), SVM	Sarcastic tweets (Ptáček et al. 2014)	50,000 non-sarcastic, 50,000 sarcastic	Developed a Deep Convolutional Neural Networks model for sarcasm detection
Sindhu et al. (2019)	Two-layered long short term memory network (LSTM), Word Embedding	A subset of Semeval-14 and academic domain dataset, English	Restaurant reviews	This study aims to evaluate faculty performance based on Students' feedback. The author utilized two-layered long short term memory networks. In the first layer, aspect is extracted and in the next layer find out the orientation

Table 10 (continued)

References	Approaches/techniques	Dataset/corpora	Data scope	Details
Xie et al. (2019)	Self-Attention Based bidirectional LSTM model, word encoder	SemEval 2014, ACL 14 and English language	Laptop and restaurant corpus, ACL 14 Twitter datasets	The author utilized a Self-Attention-Based BiLSTM model for polarity classification for short texts. The experiments are performed on SemEval 2014 (restaurant and laptop corpus) and ACL 14 (twitter datasets) datasets and results are efficient as compare with existing methods

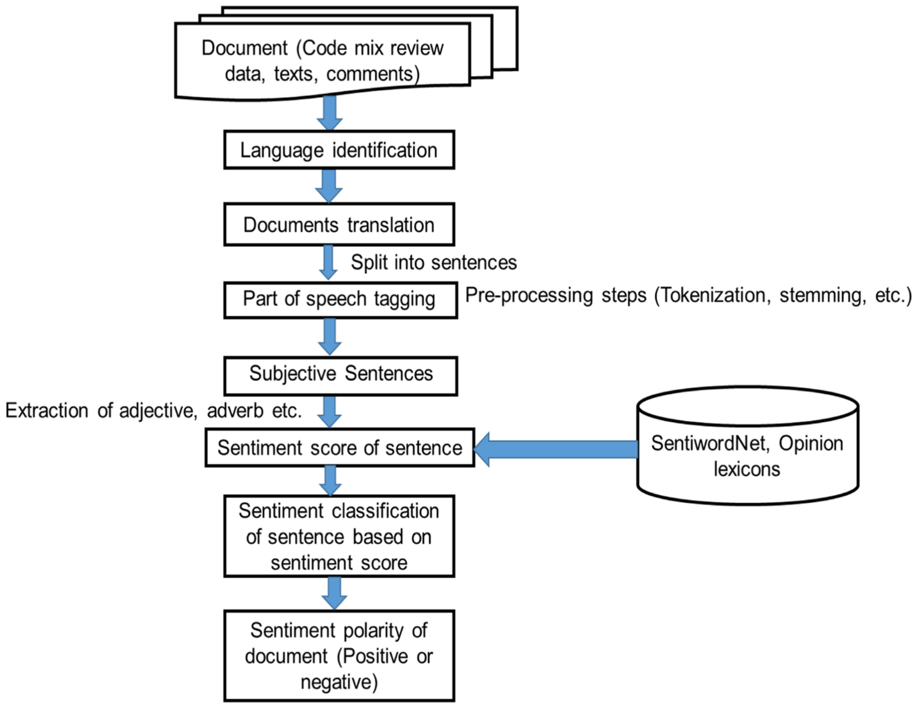

Fig. 15 Generalized process of multi-lingual opinion classification

Let's take the formal definition: D^l_{Src} denotes source domain and D^l_{trg} denotes the target domain. The set of labeled data for the source domain D^l_{Src} explained as:

$$D^l_{Src} = \left\{ \left(O^l_{s1}, P_1 \right), \left(O^l_{s2}, P_2 \right), \dots, \left(O^l_{sm}, P_m \right) \right\} \tag{1}$$

where $O^l_{s1}, O^l_{s2}, \dots, O^l_{sm}$ are m sampled review from the source domain and sentiment labels are denoted as $P_1, P_2, \ldots, P_m \in \{+1, -1\}$ where $+1$ and -1 denote the polarity i.e., positive and negative sentiments respectively.

The set of labeled data for the target domain D^l_{trg} explained as:

$$D^l_{trg} = \left\{ \left(O^l_{t1}, Q_1 \right), \left(O^l_{t2}, Q_2 \right), \dots, \left(O^l t_n, Q_n \right) \right\} \tag{2}$$

where $O^l_{t1}, O^l_{t2}, \dots, O_{tn}$ are n sampled review form target domain and sentiment labels are denoted as $Q_1, Q_2, \ldots, Q_n \in \{+1, -1\}$ where $+1$ and -1 denote the polarity i.e., positive and negative sentiments respectively. In addition to the labeled data set in source and target domain, also exist some unlabeled data set in both the domain.

The set of unlabeled data for the source domain D^U_{Src} denoted as:

$$D^U_{Src} = \left\{ O^U_{s1}, O^U_{s2}, \dots, O^U_{si} \right\} \tag{3}$$

where $O^U_{s1}, O^U_{s2}, \dots, O^U_{si}$ are i unlabeled sampled reviews.

The set of unlabeled data for the target domain D^U_{trg} denoted as:

Table 11 Compilation of research in multi-lingual opinion classification

References	Approaches/techniques	Dataset/corpora	Data scope	Details
Boiy and Moens (2009)	Maximum Entropy, Support vector machine, Multinomial Naïve Bayes (MNB), unigram, bigrams and trigrams of words	Pang and Lee (2004) v2.0, English (Review), Dutch (Forum), French (Blog)	Forum, blog, Review (2000 Movie review, fok.nl, forums. automotive.com, skyrock.com, livejournal.com, xanga.com, blogspot.com, amazon.fr, ciao.fr, kieskeurig.nl)	The First experiments are performed on Pang and Lee v2.0 dataset using different classifiers like SVM, MNB, and Maximum Entropy. The authors used different feature representations techniques like compound words and verbs, discourse features, unigrams, negation, subjectivity, adjectives, etc. along with a various combination of cascaded techniques with three single classifiers viz. Maximum Entropy, SVM, MNB, for multilingual opinion classification. For each language, they collected 750 positive and 750 negative reviews and achieved the best result using ME for French, SVM for Dutch, and MNB for English from various combinations of experiments
Mihalcea et al. (2007)	Lexicon based approach, rule-based classifier	English Romanian dictionary (41,500 entries), Universal dictionary (4500 entries)	News article, MPQA corpus, Romanian, English	To bridge the gap between the languages (English to selected target language), they utilized parallel corpora, bilingual dictionary, and rule-based classifier

Table 11 (continued)

References	Approaches/techniques	Dataset/corpora	Data scope	Details
Banea et al. (2008)	Machine translation, Lexicon based approaches, Support vector machine, and Naïve Bayes.	English (Source language), Romanian and Spanish (target language)	MPQA corpus, News article (535 English), SemCor Corpus (11,000 reviews) product review (fashion, politics, education, etc.)	The authors used machine translation, parallel corpora, SVM and Naïve Bayes classifier, to bridge the gap between languages. The result explained that SVM performs better than Naïve Bayes for cross-lingual
Duh et al. (2011)	Machine translation, adaptation algorithms, Supervised SVM, Transductive SVM	English (Target language), Japanese, French, German (Source languages)	Music, Amazon datasets (DVD, Books), Google, Bing, Microsoft translator	To mismatch, the gap between the languages, utilizes machine translation, adaptation algorithm, and Transductive SVM. The authors used source languages (Japanese, French, German), target language (English), and translation engines such as Google translator, Bing translator, Microsoft translator. From the experiments, they achieved the cross-lingual accuracies of 77% for German, 75.6% for French and 69.4% for Japanese
Gui et al. (2014)	Transductive transfer learning (TTL), unigram/bigram, and SVM^{light4}	English, Chinese, (12,000 labeled English, 120 Chinese product 94,651 unlabeled Chinese reviews)	NLP&CC 2013 (Dataset), Product Review (Music, DVD, and Book), Google translator, ICTCLAS (Chinese word segmentation tool)	Performed cross-lingual opinion analysis (CLOP) and utilized a transfer learning method for negative transfer detection and reduced 13.1% errors

Table 11 (continued)

References	Approaches/techniques	Dataset/corpora	Data scope	Details
Lambert (2015)	Statistical machine translation, Unigram, weka toolkit	English, Spanish, OpeNER opinion corpus	Hotel review in English and Spanish, monolingual data (booking.com and TripAdvisor.com)	To overcome some problems in standard machine translation, they proposed constrained statistical machine translation based aspect –level to transfer the opinion and achieve the results (from about 4 to 8% and 2.3 to 3.5% loss in accuracy) to monolingual ones
Nguyen and Le Nguyen (2018)	Bidirectional Long Short Term Memory (BiLSTM), word embedding	SenTube (10,000 Italian, 38,000 English comments)	SenTube dataset (tablets (TABLET), automobiles (AUTO))	Proposed a new model for multilingual opinion analysis on the SenTube dataset named as convolutional N-gram BiLSTM word embedding. As compared with previous work (SVM with shallow syntactic structures (STRUCT)), the proposed model performs well on the SenTube dataset
Stanik et al. (2019)	Convolutional neural networks (CNNs), Hyperparameter Tuning, supervised machine learning	Telecommunication Companies (Twitter support accounts)	Microblogs (15,000 Italian tweets, 10,000 English tweets)	To classify multilingual user feedback (English and Italian language), they compared the traditional machine learning approach with a deep learning approach and get comparable results to deep learning

Table 11 (continued)

References	Approaches/techniques	Dataset/corpora	Data scope	Details
Pessutto et al. (2019)	Medoid-based clustering algorithms, Unsupervised clustering Technique, Multilingual Aspect Clustering with k-medoids and Bisecting k-medoids	SemEval 2016—Task 5 (Russian, Spanish, Turkish English, and Dutch), Amazon dataset (Spanish, French, German, Italian and English)	Restaurant reviews (Ambience, Location, Drinks, Service, and Food), Digital Cameras (Imaging, Memory, Battery, Performance, Video, and other	In this paper, the authors worked on the task of multilingual aspect clustering and experiments are performed on the different aspects of the two publicly available datasets (Restaurant and digital cameras reviews) in different languages. They utilized an unsupervised multilingual clustering approach and results are comparable to the baseline approaches

$$D_{trg}^{U} = \left\{ O_{t1}^{U}, O_{t2}^{U}, \dots, O_{tj}^{U} \right\} \tag{4}$$

where $O_{t1}^{U}, O_{t2}^{U}, \dots, O_{tj}^{U}$ are j unlabeled sampled reviews respectively. The task of cross-domain opinion analysis is to train our n-ary classifier based on the combination of labeled and unlabeled dataset $\{D_{Src}^{l}, D_{trg}^{l}, D_{Src}^{U}, D_{trg}^{U}\}$ available in the source and target domain.

3.7.3 Basic terminologies

Pre-processing Sentiment analysis requires many pre-processing steps for structuring the text data and extracting the features. Data is collected from many sources and that text data need to be pre-processed before using it. There are several pre-processing steps used in text data such as Stop word removal, Tokenization, Parsing, Part of Speech (POS) tagging, Stemming, word segmentation, and feature extraction. We explain some general pre-processing techniques.

Stop words do not contribute to the analysis of text so we remove that stop words in the pre-processing steps. Examples of stop words are "a", "the" "as" and "on" etc. Tokenization is the process in which breaks the sentence into symbols, phrases, words, or some expressive tokens by eliminating some punctuation. In the English language, it is trivial to divide the words by the spaces. It is one of the most fundamental techniques for natural language processing tasks. With the help of a token, we can find out some additional information like name entity or opinion phrases. For tokenization, many fundamental tools are available such as OpenNLP Tokenizer, Stanford Tokenizer, etc.

Parsing and Part of Speech tagging are methods that analyze syntactic and lexical information of the text. Part of speech tagging is performed, to identify different parts of speech in the text. The POS tag is very vital for natural language processing. Part of speech tagging is used to find the equivalent POS tag for each word. POS tags such as noun, adjective, verb, adverb, a combination of two consecutive words like adverb-adjective, adverb-verb, n-gram, etc. are taken-out using the parser. Parsing is an important phase, it gives sentiment words as an output. Sentence parsing involves assigning different POS tags for the given text.

Stemming is a technique to acquire a word into its root form while discounting the different parts of speech of the word. Due to noise and sparseness in textual data, it often needs an extreme level of feature extraction that is one of the important steps in pre-processing.

Word segmentation technique is used when there are no explicit word boundary markers in the text such as Japanese, Chinese language. It is a sequential labeling problem. Several tools and approaches are available such as Stanford Segmenter, THULAC, ICTCLAS, Conditional Random Fields (CRFs), maximum-entropy Markov models, Hidden Markov models, etc. for this task.

For the pre-processing of data, some publically available toolkits are summarized in Table 12.

3.7.4 Languages and available datasets

In the field of sentiment analysis, some famous datasets, data source, sentiment lexicon, and opinion corpora are illustrated in tabular form (Table 13). These datasets are used to accomplish different tasks in sentiment analysis. English is the most frequent language that is used in different datasets (due to its availability of the resource). Research is still going

Table 12 Publicly available pre-processing toolkits for natural language processing

References	Toolkit	Dataset language	Approach/technique	Description
Bird et al. (2009)	NLTK (Implemented in Python)	English Language texts	Parsing, semantic reasoning, stemming, POS tagging, regular expression-based tagger, tokenization, named entity recognition, etc	For performing the pre-processing tasks, Natural language Toolkit (NLTK) is used. It is an open-source platform and works as an interface between many lexicons and corpus for sentiment analysis. Link: http://www.nltk.org/
O'Connor et al. (2010)	TweetMotif (Implemented in Python)	English Language texts	Tokenization and syntactic filtering, Score and filter topic phrase candidates, Merge similar topics, Group near-duplicate messages and Finalize topics	In order to achieve track political protests, summarize opinion, uncover scams and deflate rumors in real-time, TweetMotif performs tokenization of tweets, language modeling, near-duplicate detection, syntactic filtering, and set cover heuristics. Link: http://tweetmotif.com
Apache OpenNLP	OpenNLP (Implemented in Python)	English Language texts	Named entity recognition, part-of-speech tagging, sentence segmentation, tokenization, co-reference resolution, language detection, parsing, and chunking	The Apache OpenNLP is an open-source framework and performs multiple pre-processing tasks by using maximum entropy classifier. Link: https://opennlp.apache.org
Qiu et al. (2013b)	FudanNLP (Implemented in Java)	Chinese Language texts	Chinese Word Segmentation, Named Entity Recognition, Dependency parsing, Temporal Phrase Recognition and Normalization, Anaphora Resolution, and Chinese POS tagging	The FudanNLP is an open-source framework and performs multiple pre-processing tasks for the Chinese language by using rule-based and statistics-based methods. Link: https://code.google.com/archive/p/fudannlp/

Table 12 (continued)

References	Toolkit	Dataset language	Approach/technique	Description
Manning et al. (2014) and java	Stanford CoreNLP (Implemented in Java)	Arabic, Chinese*, English, French*, German* text languages	Tokenization, sentence splitting, POS tagging, Morphological Analysis, Named Entity Recognition, Syntactic Parsing, coreference resolution, and Other annotators	The Stanford CoreNLP is an open-source framework and performs multiple pre-processing tasks by using maximum entropy model, Conditional random field and deep learning. It supports more languages such as Arabic, Chinese*, English, French*, and German*. Where * indicates tool can perform the partial task, not all the tasks. Link: http://stanfordnlp.github.io/CoreNLP/
Gimpel et al. (2011), Derczynski et al. (2013)	POS tagger (Implemented in Python)	English Language texts	Part-of-speech tagger, tokenizer, dependency parser for unlabeled tweets, and hierarchical word clusters	The POS tagger is an open-source framework and performs multiple pre-processing tasks for micro-blog English language. Link: http://www.cs.cmu.edu/~ark/TweetNLP/
Kong et al. (2014)	TweeboParser (Implemented in Python)	English Language texts	Tweet dependency parser for English, multiword expressions, and token selection	The TweeboParser is an open-source framework and performs tweet dependency parser for microblog English language using statistical parsing language. Link: http://www.cs.cmu.edu/~ark/TweetNLP/
Rehurek and Sojka (2010)	Gensim (Implemented in Python)	English Language texts	Hierarchical Dirichlet Process, Random Projection, Latent Dirichlet Allocation (LDA), Latent Semantic Analysis (LSA), and word2vec	The Gensim is an open-source software framework and performs topic modeling using large-scale corpora. Link: http://radimrehurek.com/gensim/

Table 12 (continued)

References	Toolkit	Dataset language	Approach/technique	Description
Che et al. (2010)	LTP (Implemented in C++/Python)	Chinese Language texts	Name Entity recognition, POS tagging, Word segmentation, semantic role labeling, word sense disambiguation	The Language Technology Platform is an open-source software framework and performs multiple preprocessing tasks such as lexical analysis, syntactic parsing, and semantic parsing for Chinese NLP. Link: http://www.ltp-cloud.com/intro/en/
Zhu and Wang (2015)	NiuParser (Implemented in C++)	Chinese Language texts	Word segmentation, dependency parsing, semantic role labeling, named entity recognition, constituent parsing, and shallow syntactic parsing (chunking).	The NiuParser is an open-source software framework and perform multiple preprocessing task such as Syntactic and Semantic Analysis for Chinese NLP using Conditional Random Fields, Maximum Entropy and Recurrent Neural Networks and support Software Development Kit (SDK) interfaces for system speed-up. Link: http://www.niuparser.com/index.en.html
Toutanova et al. (2003)	Stanford Log-linear Part-Of-Speech Tagger (Implemented in Java)	English Language texts	Parts of speech tagger, dependency network representation, use of lexical features consecutive words, and fine-grained modeling.	The Stanford Log-linear Part-Of-Speech Tagger is an open-source software framework and performs multiple preprocessing tasks with an accuracy of 97.24%. Link: https://nlp.stanford.edu/software/tagger.shtml

Table 12 (continued)

References	Toolkit	Dataset language	Approach/technique	Description
Porter (2001)	Snowball (Implemented in Java)	English Language texts	Stammer	The Snowball is an open-source software framework and performs stammer for English texts. Link: http://snowball.tartarus.org/runtime/use.html
Kevin Atkinson (2006)	GNU Aspell (Implemented in C++)	English Language texts	Spell checker	The GNU Aspell is an open-source software framework and performs spell checker for English texts. Link: http://aspell.net/

Table 13 Publicly available datasets

References	Data sources/dataset domain	Dataset language	Details
Blitzer et al. (2007)	Amazon product reviews (kitchen, DVDs, book, and electronics)	English	Amazon Product reviews on 4 different domains named as Books, DVDs, Kitchen, Electronics and number of features are 188,050, 179,879, 89,478, and 104,027 with an average length of per review 239, 234, 131, and 153 respectively Resource: http://www.cs.jhu.edu/mdredze/datasets/sentiment/
Lang (1995)	Newsgroups (news domain)	English	It contains 18,000 newsgroup reviews on 20 subcategories approximately Resource: http://people.csail.mit.edu/jrennie/20Newsgroups
Wu and Tan (2011)	Book domain (book review)	Chinese	From web source, www.dangdang.com/, Comprise approximately 4000 annotated book posts with 2000 negative and 2000 positive reviews Resource: www.searchforum.org.cn/tansongbo/corpus/Dangdang_Book_4000.rar
Pang et al. (2002)	Movie domain (movie review)	English	It contains labeled movie reviews with respect to sentiment polarity and rating Link: http://www.cs.cornell.edu/people/pabo/movie-review-data/
Wang et al. (2010)	Hotel domain (hotel review/rating, forums)	English	From the resource TripAdvisor, Comprise approximately 235,793 hotel review in one month form (from February 14, 2009, to March 15, 2009) and consider the 7 aspect rating in each review such as Business service, Service, Check-In/Front Desk, Cleanliness, Location, Room and value Link: http://times.cs.uiuc.edu/~wang296/Data
Jo and Oh (2011)	Online review (electronics and restaurants domain)	English	Collected 22,000 total electronics reviews from web source http://www.amazon.com and 30,000 restaurant reviews from web source http://www.yelp.com Link: http://uilab.kaist.ac.kr/research/WSDM1

Table 13 (continued)

References	Data sources/dataset domain	Dataset language	Details
Hu and Liu (2004)	Bing Liu's opinion lexicon (customer Review on 5 different electronics product: 1 cellular phone, 1 MP3 player, 1 DVD player, and 2 digital camera)	English	Collected the first 100 reviews for each product from web source http://www.amazon.com and https://www.cnet.com/ Link: https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html "further improved this lexicon by (Ding, Liu, and Yu, WSDM-2008)"
Cruz et al. (2010)	TBOD corpus on product review (car, headphone, and hotel)	English	Collected the 972 car reviews, 988 hotel reviews and 587 headphone reviews from web source http://www.epinions.com Link: http://www.lsi.us.es/~fermin/index.php/Datasets
Demirtas (2013)	Movie domain and multi-domain corpus (Product review (books, DVDs, kitchen and electronics domain)	English and Turkish	From the web source http://www.beyazperde.com, Collected the 5331 positive and 5331 negative Turkish movie reviews and from the web source http://www.hepsiburada.com, Collected the 700 positive and 700 negative Turkish reviews for each domain with the scale 1–5 Movie and multi-domain datasets link: http://www.win.tue.nl/~mpechen/projects/smm/#Datasets
Zhang et al. (2011)	Restaurant corpus (restaurant Review)	Cantonese	Collected 1500 positive and 1500 negative Cantonese-written reviews and created a restaurant Cantonese corpus Link: http://www.openrice.com
Camp and Bosch (2012)	Biographical articles	Dutch	They used the Biographical Dictionary of Socialism and the Labour Movement in The Netherlands (BWSA) as input that comprises 574 articles written in 200 different authors in the Dutch language Link: https://socialhistory.org/bwsa

Table 13 (continued)

References	Data sources/dataset domain	Dataset language	Details
Reyes and Rosso (2012)	Ironic dataset (5 Different product Milk, T-shirt, Zubaz Pants, Uranium Ore and Platinum Radiant Cut 3-Stone)	English	Collected 3163 positive reviews from 5 different product named as Milk, T-shirt, Zubaz Pants, Uranium Ore and Platinum Radiant Cut 3-Stone form amazon and collected negative reviews, from some different domain like Book, Camera, CD, Toy, and Videogame console from amazon.com, funny community-driven from Slashdot.com and hotel reviews from TripAdvisor.com Link: http://users.dsic.upv.es/grupos/nle/
Kouloumpis et al. (2011)	HASH, EMOT and ISIEVE datasets (tweets, tweets + emoticons)	English	1. Hashtagged data set (HASH) contained total 222,570 tweets, in that 125,859 Neu tweets (57%), 64,850 Neg tweets (29%), and 31,861 Pos tweets (14%). Link: http://demeter.inf.ed.ac.uk 2. Emoticon Dataset (EMOT) contained total 381,381 tweets, in that 230,811 (61%) Pos tweets and 150,570 (39%) Neg tweets Link: http://twittersentiment.appspot.com 3. iSieve data set contained total 4015 tweets, in that 2295 Neu tweets (57%), 200 Neg tweets (5%), and 1520 Pos tweets (38%) Link: www.i-sieve.com
Walker et al. (2012)	Internet Argument Corpus (deliberation and debate)	English	Extracted the discussion from web source 4forums.com. Collected 390, 704 posts in 11, 800 discussions (aka threads) by 3, 317 authors Link: https://nlds.soe.ucsc.edu/iac
Costa et al. (2014)	Spam tips (spam reviews)	English	Contained 400 truthful reviews and 400 deceptive reviews in the negative and positive category. Link: http://myleott.com/op-spam.html

Table 13 (continued)

References	Data sources/dataset domain	Dataset language	Details
Go et al. (2009)	Stanford Twitter dataset test set (STS) (Tweets on different topics with Emoticons)	English	Collected 177 positives and 184 negatives tweets from different topics The Twitter API link: http://apiwiki.twitter.com/ The Stanford Classifier link: http://nlp.stanford.edu/software/classifier.shtml. and Corpus Link: http://cs.stanford.edu/people/alecmgo/trainingandtestdata.zip
Maas et al. (2014)	Stanford large movie dataset (movie review)	English	Collected 50,000 unlabeled movie reviews along with 25,000 labeled reviews form web source https://www.imdb.com/ Link: http://ai.stanford.edu/~amaas/data/sentiment/
Kontopoulos et al. (2013)	Twitter (smartphones tweets)	English	Collected hashtag tweets on a smartphone. Link: http://goo.gl/UQvdx
Cambria et al. (2015)	Opinion datasets (patient opinions)	English	Collected 2000 patient opinions post on health services such as Staff, timelines, parking, food, communication, and clinical service Link: http://patientopinion.org.uk
Agarwal et al. (2011)	Twitter dataset (tweets)	English	Acquired 11,875 manually annotated tweets. Link: deepak.mittal@ngicorportion.com
Wiebe et al. (2005)	MPQA opinion corpora (Multi-Perspective Question Answering (MPQA), News article)	English	From 187 different NEWS sources, collected 10,657 sentences in 535 documents Link: http://mpqa.cs.pitt.edu/corpora/mpqa_corpus/
Wilson et al. (2005)	MPQA Subjectivity Lexicon (Subjective lexicon)	English	The lexicon contains approximately 8000 words with their polarities and subjective information like weak or strong Link: http://mpqa.cs.pitt.edu/lexicons/subj_lexicon/
Baccianella et al. (2008)	SentiWordNet 3.0 Lexicon (Lexicon resource)	English	It is an enhanced lexicon resource of SentiWordNet 1.0. It is freely available in Link: https://sentiwordnet.isti.cnr.it/ with subjective information as positivity, negativity, and neutrality

Table 13 (continued)

References	Data sources/dataset domain	Dataset language	Details
Ku and Chen (2007)	NTUSD sentiment lexicons (Lexicon resource)	Chinese	National Taiwan University Semantic Dictionary is a collection of 2812 and 8276 positive and negative traditional and simplified Chinese words Link: http://academiasinicanlplab.github.io/, https://rdrr.io/rforge/tmcn/man/NTUSD.html
Chen et al. (2010)	E-HowNet sentiment lexicons (Lexicon resource)	Chinese and English	E-HowNet includes 8945 English words and 8942 Chinese words in their English/Chinese dictionary Link: http://www.keenage.com/html/e _ index.html
Pennebaker et al. (2015)	LIWC sentiment lexicons (Linguistic Inquiry and Word counts lexicons)	English	LIWC includes some categorized regular expressions and opinion as Negate" and "Anger". Link: http://liwc.wpengine.com
Stone et al. (1966)	HGI Sentiment Lexicons (Harvard General Inquirer sentiment lexicons)	English	It included 2291 negative words and 1915 positive words from 182 categories Link: http://www.wjh.harvard.edu/~inquirer/
TripAdvisor review dataset	Hotel and Restaurant	Spanish	Contain approximately 18,000 customer reviews from H-opinion Link: http://clic.ub.edu/corpus/es/node/106
ICWSM 2011 Spinn3r Dataset	Multi-Domain	English	Include 386 million reviews from a different domain such as a forum, a news article, blog post, and social media. Link: http://www.icwsm.org/2011/data.php
COAE2008	Product reviews	Chinese	Contained multi-domain such as a computer, mobile phone, house, economics, finance, education, and movie Link: http://ir-china.org.cn/coae2008.html
Tsai et al. (2014)	Manually annotated datasets (Product Review (Hotels, Movies, and Restaurants))	Chinese	Included 10,000 reviews individual from a different source for a different domain. They collected reviews from agoda.com, atmovies.com.tw, and iPeen.com.tw for Hotels, Movies, and Restaurants
Tsakalidis et al. (2014)	Emoticons dataset "ED" (Emoticon Tweets)	English	Collected happy/sad emoticons (":)", ":(" from 250,000 tweets written in the English language. Link: https://github.com/socialsensor/sentiment-analysis

Table 13 (continued)

References	Data sources/dataset domain	Dataset language	Details
Obama Healthcare reform (HCR), Obama-McCain debate (OMD)	Healthcare and Debate	English	Collected 1889 Tweets from Barrack Obama's healthcare reform presented in 2010 and Collected 3269 labeled tweets from Obama and McCain debate. 133 k English words http://www.speech.cs.cmu.edu/cgi-bin/cmudict Available data: https://bitbucket.org/speriosu/updown/src Subjective lexicon: https://mpqa.cs.pitt.edu/opinionfinder/opinionfinder_2/

on for the non-English language and it is a very challenging task to create lexicon, corpora, and resources for the different languages. Non-English language includes language such as Chinese, German, Hindi, Spanish, French, etc.

4 Baseline methods and techniques for cross-domain opinion classification

This section explains an outline of baseline methods and techniques of cross-domain opinion classification in the early days. Transfer learning and Domain adaptation or knowledge adaptation play an important role in the field of cross-domain opinion classification. In cross-domain opinion classification, trained a machine based on the available labeled/unlabeled dataset of source and target domain and test that machine on different domain whether machine work properly or not. In the early reviews, most of the articles used the amazon multi-domain dataset. Amazon multi-domain dataset consists of four different types of domains such as Kitchen, electronics, DVDs, and Books with 89,478, 104,027, 179,879, and 188,050 number of features respectively. The key techniques or approaches for the cross-domain opinion classification are explained in the following Fig. 16.

4.1 Structured Correspondence Learning (SCL) Technique

The SCL technique was introduced by:

Blitzer et al. (2006)

Approach: Structured Correspondence Learning, Support vector machine, part of speech tagging and Amazon multi-domain datasets (English language)
Corpora: Kitchen, DVD's, electronics and Books
Explanation: In order to encourage communication among features from a variety of domains, a structured correspondence learning algorithm is introduced. The vital role of structure corresponding learning is to recognize correspondences among associations related to features and pivot features. Pivot features are features that act as a similar mode in both domains for discriminative learning. In their experiment, they considered the unlabeled data from the source and target domain and labeled data from the source domain. By using this dataset, structure correspondence learning outperformed with the semi-supervised and supervised learning approach. This work is extended by Blitzer et al. (2007).

Blitzer et al. (2007)

Approach: Structured Correspondence Learning with mutual information (unigram or bi-gram and domain label), Support vector machine, part of speech tagging and Amazon multi-domain datasets (English language)
Corpora: Kitchen, DVD's, electronics and Books

Fig. 16 Techniques of Cross-domain opinion classification

Explanation: Structured correspondence learning depends on the selection of pivot features, and if pivot features are not well-selected that can directly change or alter the performance of a classifier. To overcome this problem, they extend the existing algorithm as Structured correspondence learning with mutual information (SCI-MI). For cross-domain opinion classification, structured corresponding learning with mutual information (SCI-MI) is more suitable as a comparison with Structural corresponding learning because it is selecting top pivot features by using mutual information between a domain label and uni-gram or bi-gram features. To measure the loss between the domains due to adaptation from one domain to another domain, they evaluated the A-distance. Using unlabeled data, A-distance is measured that will help to find out the divergence that affects the classification accuracy. Most recently the concept of Blitzer et al. (2006) is borrowed by Yu and Jiang (2016).

Yu and Jiang (2016)

Approach: Neural network, Sentence Embeddings, Deep learning (Convolutional Neural Networks and Recurrent Neural Network), Movie dataset (Pang and Lee

2004)[1] and Movie (Socher et al. 2013)[2] datasets, Digital products (Camera, MP3) (Hu and Liu 2004),[3] and Laptop and Restaurant SemEval (2015) (English language)
Corpora: Five benchmark product review, word embeddings from word2vec[4]
Explanation: For domain adaptation, they induced a sentence embedding based on two auxiliary tasks (Sequential-auxiliary and Joint-auxiliary). The experiments are performed on five benchmark datasets and the proposed joint method outperformed several baseline methods.

4.2 Spectral feature alignment (SFA) technique

The spectral feature alignment technique is introduced by:

Pan et al. (2010)

Approach: Spectral feature alignment and Amazon multi-domain datasets, yelp and Citysearch websites (English language)
Corpora: Kitchen, DVD's, electronics, Books, video game, electronics and software from Amazon, hotel from Yelp and CitySearch
Explanation: Proposed a new algorithm Spectral feature alignment (SFA), to bridge the gap between the two different domains. The spectral feature alignment algorithm is used to align domain-specific words (collected from different domains) into unified clusters and domain-independent words work as a bridge. The proposed framework includes the spectral feature alignment algorithm and graph construction, for reducing the gap between different domains. To construct the bipartite graph, they used co-occurrence information between domain-independent words and domain-specific words. Domain-specific words and domain-independent words are two different categories of words that are used in cross-domain sentiment data. The bipartite graph uses a spectral clustering algorithm, to co-align domain-independent words and domain-specific words into a unified word cluster and to minimize the mismatches between both domain and domain-specific words. The spectral feature alignment approach outperformed as compared with an existing approach like SCL etc. Later this work is extended by Lin et al. (2014).

Lin et al. (2014)

Approach: Spectral feature alignment, Support vector machine, taxonomy-based regression model (TBRM) and cosine function and Amazon multi-domain datasets (English language)
Corpora: Kitchen, Electronics, DVDs and Books
Explanation: Introduced two approaches taxonomy-based regression model (TBRM) and a cosine function to choose the most similar models based on the target node. They also utilized the support vector machine classifier, domain adaptation algorithm (spectral feature alignment) and weight adjustment technique. The experimental results showed that proposed approaches outperformed baseline approaches. Recently in cross-domain opinion classification.

1 https://www.cs.cornell.edu/people/pabo/movie-review-data/.
2 http://nlp.stanford.edu/sentiment/.
3 http://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html.
4 https://code.google.com/p/word2vec/.

Deshmukh and Tripathy (2018)

Approach: Modified Maximum Entropy for classification, bipartite graph clustering, and POS + unigram and Amazon Product Review (English language)
Corpora: Kitchen, Electronics, DVDs and Books
Explanation: Utilized semi-supervised approach (bipartite graph clustering and modified maximum entropy (enhanced the entropy with modified increment quantity)) for classifying and extracting the opinion or sentiment words from one domain (using set of labeled lexicon from source domain) and analyze the sentiment or opinion words of another domain (labeled and unlabeled from target domain). The authors classified their methodology in two phases. In the first phase, pre-processing steps of datasets (part of speech tagging using Stanford parser) are performed and secondly, they used classifier (modified maximum entropy for classification of opinions and all tagged words after the POS tagging) and clustering (using bipartite graph) on datasets. In the experiment, they used four different product domain reviews (DVD, Book, Kitchen appliances and Electronics) and the result demonstrated that the proposed approach performs better than the other baseline methods. They also used the F-measure and accuracy for analyzing the algorithm performance. They performed 4 different experiments and found that the proposed approach performs better than the existing approach and achieve accuracy between 70% and 88.35%.

4.3 Joint sentiment-topic (JST) technique

He et al. (2011)

Approach: Modified Joint sentiment topic, Maximum Entropy from MALLET, Bag of Word and Amazon multi-domain datasets, MPQA subjectivity lexicon (English language)
Corpora: Kitchen, Electronics, DVDs and Books
Explanation: Introduced the modified Joint Sentiment Topic model that is incorporated with word polarity. The Joint Sentiment Topic model is based on/extension of Latent Dirichlet Allocation (LDA) to extract the opinion and topic simultaneously from the text. The joint sentiment model is a probabilistic model based on polarity-bearing topics, to enhance the feature space and learning is based on prior information about the domain-independent polarity words. With the help of the joint sentiment topic approach, they performed polarity word extraction on the combined data sets and transfer learning or domain adaptation on amazon multi-domain data sets. The experiment results showed that the proposed joint sentiment topic method outperforms structured corresponding learning on average and gets comparable results to spectral feature alignment. Further JST model was improved by He et al. (2013).

He et al. (2013)

Approach: Dynamic Joint sentiment topic, expectation–maximization (EM), Part of speech tagging, Unigrams + phrases and Mozilla Add-ons web site,[5] MPQA subjectivity lexicon (English language)

[5] https://addons.mozilla.org/.

Corpora: Personas Plus, Fast Dial, Echofon for Twitter, Firefox Sync, Video DownloadHelper, and Adblock Plus

Explanation: To overcome the issue in joint sentiment topic model such as static co-occurrence pattern of words in text and fitting large scale data, proposed dynamic joint sentiment topic model (dJST). The proposed approach permits the recognition and tracing of opinions of the present and regular interests and shifts in topic and sentiment. To update the dJST model using the afresh-arrived data and online inference procedures utilized the expectation–maximization (EM) algorithm. Both topic and sentiment dynamics are recognized by supposing that the present sentiment-topic specific word distributions are produced according to the word distributions at prior epochs. To obtain information on these dependencies, they utilized three different approaches: a skip model, the sliding window, and a multiscale model. The experiment showed that both the skip model and multiscale model is better than the sliding window for sentiment classification.

4.4 Active learning and deep learning approach

Active and deep learning techniques are used to select the data from which they can learn and perform effectively in less training. To acquire the preferred outputs at new data points, the active learning approach can interactively query the information source that is a special case of semi-supervised machine learning. To acquire the additional labeled target domain data, active learning uses the source domain information. In the active learning approach, three types of scenarios (pool-based sampling, stream-based selective sampling and membership query synthesis) and query strategies are used. On the other side, deep learning is the unsupervised approach, using an unlabeled dataset intending to mining the good features and obtain meaningful sentiments. In cross-domain opinion classification, very few research studies used the concept of active and deep learning. Some research studies are:

Li et al. (2013)

Approach: Query-by-Committee (QBC), label propagation (LP), Bag of words (Unigram and bigram), maximum entropy (ME), Mallet Toolkits[6] and Amazon multi-domain datasets (English language)

Corpora: Kitchen, DVD’s, electronics and Books

Explanation: For sentiment classification and informative sample selection, they introduced the active learning approach incorporates with Query By Committee (QBC). The two classifiers (source classifier utilized source domain labeled data and target classifier utilized target domain labeled data) are trained by completely exploiting the unlabeled data in the target domain with the proposed label propagation (LP) approach and utilized Query-By-Committee (QBC) for selection of informative samples. In the experiment, they considered four different product domains Kitchen, Electronics, DVDs and Books. The proposed approach outperformed the state-of-the-art. Further active learning approach used by Tsai et al. (2014).

[6] http://mallet.cs.umass.edu/.

Tsai et al. (2014)

Approach: Query-by-Committee (QBC), Bag of words (Unigram and bigram) and Chinese language
Explanation: To identify the opinion words, used active learning approach incorporates with Query By Committee (QBC).

Glorot et al. (2011)

Approach: Deep learning, Stacked Denoising Autoencoder (SDA) with rectifier units, linear SVM with squared hinge loss and Amazon multi-domain datasets (English language)
Corpora: Kitchen, DVD's, electronics and Books
Explanation: For Domain adaptation in opinion classification, they utilized a deep learning approach based on Stacked Denoising Auto-Encoders with sparse rectifier units and a linear support vector machine is trained on the transformed labeled data of the source domain. The experiment results show that the proposed approach outperforms the current state-of-the-art and comparable results to SCL, SFA, and MCT. Later deep learning approach is utilized by Nozza et al. (2016).

Nozza et al. (2016)

Approach: Deep learning, marginalized Stacked Denoising Autoencoder (mSDA), Ensemble learning Methods (Bagging, Boosting, Random SubSpace and Simple Voting) and Amazon multi-domain datasets (English Language)
Corpora: Kitchen, DVD's, electronics and Books
Explanation: Proposed a new framework based on deep learning and ensemble methods for domain adaptation. In this framework, deep learning is used for obtaining high-level features of cross-domain and ensemble learning methods are used for minimizing the cross-domain generalization error. The experiments are performed on amazon multi-domain datasets and the proposed approach outperformed the current state of art approaches. Further deep learning is used for domain adaptation by Long et al. (2016).

Long et al. (2016)

Approach: Deep learning, Transfer Denoising Autoencoder (TDA), deep neural networks, multi-kernel maximum mean discrepancy (MK-MMD), TF-IDF and Amazon multi-domain datasets, Email Spam Filtering Dataset,[7] Newsgroup Classification Dataset,[8] Visual Object Recognition Dataset (English language)
Corpora: Kitchen, DVD's, electronics, books, Public and user email, Amazon, Webcam, DSLR and Caltech-256
Explanation: The proposed framework outperformed state of the art methods on different adaptation tasks such as visual object recognition, newsgroup content categorization, email spam filtering, and sentiment polarity prediction on multi-domain datasets.

[7] http://www.ecmlpkdd2006.org/challenge.html.
[8] http://people.csail.mit.edu/jrennie/20newsgroups.

4.5 Topic modeling

In order to minimize the high dimensionality in a term-document matrix into low dimensions, utilized the Topic modeling approaches that are using the concept of latent semantic indexing and clustering techniques. Some research on these categories are:

Wu and Tan (2011)

Approach: SentiRank algorithm, manifold-ranking algorithm, Bag of words, Chinese text POS tool-ICTCLAS[9] and Chinese domain-specific data sets Book,[10] Hotel[11] and Notebook[12] (Chinese language)
Corpora: Book,[13] Hotel[14] and Notebook[15]
Explanation: To overcome the problem of domain adaptation in sentiment analysis, proposed a two-stage framework where the first stage is "building a bridge stage" (by applying the SentiRank algorithm) and the second stage is "following the structure stage" (by employing the manifold-ranking process). In the first stage, they build the bridge to collect some confidently labeled data from target data and reduce the gap between the source domain and target domain. Whereas in the second stage, they used the manifold-ranking algorithm and the manifold-ranking scores for utilizing the intrinsic structure collectively revealed by the target domain and to label the target-domain data. For the experiment, they considered Chinese domain-specific dataset on Books, Hotels, Notebook domain and compared the proposed framework with baseline methods (Proto, transductive SVM (TSVM), SentiRank algorithm, expectation–maximization (EM) algorithm based on Proto, expectation–maximization (EM) algorithm based on SentiRank, and Manifold based on Proto) and shown the comparable results. Later in topic modeling:

Roy et al. (2012)

Approach: Online Streaming Latent Dirichlet Allocation (OSLDA), Learning Transfer Graph Spectra, SocialTransfer: Transfer Learning from Social Stream, Bag of words, and Microblogs (English language)
Corpora: YouTube and NIST Twitter dataset
Explanation: Based on social streams (by employing Online Streaming Latent Dirichlet Allocation (OSLDA)), proposed a new framework for cross-domain opinion classification named as *SocialTransfer*. To acquire knowledge from cross-domain data, *SocialTransfer* is used in numerous multimedia applications. In their experiment consider real-world large-scale datasets like 10.2 million tweets from NIST Twitter dataset (Worked as source domain) and 5.7 million tweets from YouTube (Target domain) and proposed approach *SocialTransfer* outperformed traditional

9 http://ictclas.org/.
10 www.searchforum.org.cn/tansongbo/corpus/Dangdang_Book_4000.rar.
11 www.searchforum.org.cn/tansongbo/corpus/Ctrip_htl_4000.rar.
12 www.searchforum.org.cn/tansongbo/corpus/Jingdong_NB_4000.rar.
13 http://www.dangdang.com/.
14 http://www.ctrip.com/.
15 http://www.360buy.com/.

learners significantly. Further, to identify the properties and common structure used in different domain directly and indirectly explained by Yang et al. (2013).

Yang et al. (2013)

Approach: Probabilistic Link-Bridged Topic (LBT) Model, expectation–maximization (EM), Probabilistic Latent Semantic Analysis (PLSA), Support vector machine and Global domain[16] and scientific research papers (English language)
Corpora: Industry Sectors dataset (topic include—computer science research papers dataset (Data structure, encryption, and compression, networking, operating system, machine learning, etc.))
Explanation: Proposed a new model named Link-Bridged Topic (LBT) for transfer learning in cross-domain. In this model, firstly identify the direct or in-direct co-relation, properties and common structure among the documents by using an auxiliary link network. Secondly, Link-Bridged Topic (LBT) concurrently wraps the link structures and content information into a unified latent topic model. The aim of Link-Bridged Topic (LBT) is to bridge the gap across different domains. In their experiment, considered two different domain such as scientific research papers datasets and web page datasets and proposed model suggestively improves the generalization performance. Further in topic modeling indirectly work is extended by Zhao and Mao (2014).

Zhao and Mao (2014)

Approach: Supervised Adaptivetransfer Probabilistic Latent Semantic Analysis (SAtPLSA), Probability Latent Semantic Analysis (PLSA), expectation–maximization (EM) and 20Newsgroups[17] and Reuters-21,578[18] (English Language)
Corpora: 20 subcategories of newsgroup and Retures21,578[19]
Explanation: To overcome the issue in knowledge transfer like partial utilization of source domain's labeled information and exploit source domain's knowledge in the later stage of the training process, introduced a new model named Supervised Adaptivetransfer Probabilistic Latent Semantic Analysis (SAtPLSA). It is an extended version of Probability Latent Semantic Analysis (PLSA). To learn the model parameters, they used the expectation–maximization (EM) approach. In their experiments, they considered nine benchmark datasets (20 Newsgroups and Reuters-21578) and compare the proposed approach with five state-of-art domain adaptation approaches (Partially Supervised CrossCollection LDA (PSCCLDA), Collaborative Dual-PLSA (CDPLSA), Topic-bridge PLSA (TPLSA), Spectral Feature Alignment (SFA), and Topic Correlation Analysis (TCA)) and two classical supervised learning methods (Logistic Regression (LR) and Support Vector Machines (SVM)) and get the effective results. Further in topic modeling:

Zhou et al. (2015)

16 http://people.cs.umass.edu/~mccallum/data.html.
17 http://people.csail.mit.edu/jrennie/20Newsgroups.
18 http://www.daviddlewis.com/resources/testcollections.
19 http://www.cse.ust.hk/TL/dataset/Reuters.zip.

Approach: Topical correspondence transfer (TCT), Support Vector Machine (SVM), Bag of words (Unigram and bigram) and Amazon multi-domain datasets (English language)
Corpora: Kitchen, DVD's, electronics and Books
Explanation: Proposed a new model or algorithm named Topical correspondence transfer (TCT), to bridge the gap between different domains in which labeled data is available only in the source domain. Topical correspondence transfer (TCT) assumes that there exists a set of shared topics and domain-specific topics for the target and source domain. In order to reduce the gap between the domains with the help of shared topics, Topical correspondence transfer (TCT) learns domain-specific information from different domains into unified topics. The experiments are performed on amazon multi-domain datasets and the results of TCT are compared with *SCL*, *SFA*, and *NMTF* for cross-domain opinion classification. Topical correspondence transfer (TCT) gets significant improvements through with state-of-the-art methods. Later in topic modeling

Liang et al. (2016)

Approach: Latent sentiment factorization (LSF), A Library for Support Vector Machine (LIBSVM),[20] Unigram and bigram, Word2Vec,[21] probabilistic matrix factorization and Amazon multi-domain datasets (English Language)
Corpora: Kitchen, DVD's, electronics and Books
Explanation: Proposed a new algorithm based on the probabilistic matrix factorization approach named Latent sentiment factorization (LSF), to adopt opinion associations of words more efficiently and to bridge the gap between the domains in cross-domain opinion classification. Latent sentiment factorization first maps the documents and the words in source and target domains into a unified two-dimensional space based on domain shared words, after that they employed labeled document's sentiment polarities in the source domain and prior opinion information of words to constrain the latent space. In his experiments, they used amazon multi-domain datasets and the proposed approach performed well compare with five baseline techniques including NoTransf, Upperbound, SCL, SFL, and TCT. Most recently the work is extended by Wang et al. (2018a, b).

Wang et al. (2018a, b)

Approach: Sentiment Related Index (SRI), pointwise mutual information (PMI), Support Vector Machine (SVM) Unigram and bigram, SentiRelated algorithm and Rew Data, DoubanData dataset (Chinese language)
Corpora: Rew Data (Computer, Hotel, Education), Douban data (Books, Music, and Movie)[22] and sentiment lexicons (NTUSD),[23] HowNet[24]
Explanation: In order to measure the correlation between different lexical features in a precise domain, sentiment related index (SRI) is created and based on SRI the authors proposed a new algorithm named SentiRelated. By using this approach, they

[20] http://www.csie.ntu.edu.tw/cjlin/libsvm/.
[21] http://word2vec.googlecode.com/svn/trunk/word2vec.c.
[22] http://www.douban.com/.
[23] http://www.datatang.com/data/44317.
[24] http://www.datatang.com/data/12990.

bridge the gap between source and a target domain and validate the novel approach on two different datasets (RewData, DoubanData dataset) in the Chinese language. The experiment results explained that the SentiRelated algorithm performs well to analyze the opinion polarity.

4.6 Thesaurus-based techniques

To transfer the knowledge, introduced a new approach "*thesaurus*" in cross-domain sentiment classification.

Bollegala et al. (2013)

Approach: Sentiment Sensitive Thesaurus (*SST*), Query Expansion, Pointwise Mutual Information (*PMI*), L1 regularization logistic regression,[25] POS tagging+ (Unigram and bigram), rating information and Amazon multi-domain datasets (English Language)
Corpora: Kitchen, DVD's, Electronics and Books
Explanation: Proposed a new approach for the cross-domain sentiment classification named as Sentiment Sensitive Thesaurus (*SST*). Firstly, they used the labeled datasets from the source domain and unlabeled datasets from both source and target domains and created a sentiment sensitive distributional thesaurus. After that, they used the created thesaurus and expand the feature vector (query expression) at the time of training and testing on the L1 regularized logistic regression-based binary classifier. The proposed approach outperformed as compare with numerous previously cross-domain approaches and baseline methods for multi-source as well as single-source domain adaptation settings along with supervised and unsupervised domain adaptation approaches. Moreover, the authors compared the proposed approach with the lexical resource of word polarity, i.e., SentiwordNet,[26] and showed that the created thesaurus accurately pick up the words that expressed similar opinions. Further Sanju and Mirnalinee (2014) enhanced the work of Bollegala et al. (2013) and used the Wiktionary in sentiment sensitive thesaurus (*SST*) in order to reduce the mismatch between the domain. Later in cross-domain sentiment classification using thesaurus (Jimenez et al. 2016) suggested the framework.

Jimenez et al. (2016)

Approach: Bootstrapping algorithm (BS), Term Frequency (TF), POS tagging, (Unigram and bigram) and Spanish MuchoCine corpus (MC), iSOL Spanish polarity lexicon (Spanish language)
Corpora: Movie
Explanation: For the transfer learning of a polarity lexicon, introduced two corpus-based techniques that are language independent and work in any domain. One corpus-based technique based on term frequency (*TF*) achieves very promising results by using previously polarity tagged documents. Another corpus-based technique (did not want an annotated corpus) based on the bootstrapping algorithm (BS) improves on the baseline system. To achieve the benefit of the positive features of each of

[25] http://www.chokkan.org/software/classias/.
[26] http://sentiwordnet.isti.cnr.it/.

them, they combined both methods and get an improvement of 11.50% in terms of accuracy. Recently in cross-domain sentiment classification using thesaurus technique:

Bollegala and Mu (2016)

Approach: Rule-based modeling, K-NN, Pointwise Mutual Information (PMI) based pivot selection, a numeric Python library for decomposition,[27] L2 regularization logistic regression in scikit-learn,[28] POS tagging + (Unigram and bigram), rating information and Amazon multi-domain datasets (English language)
Corpora: Kitchen, DVD's, Electronics and Books
Explanation: Developed an embedding technique for the training phase of cross-domain opinion classification that considered following objective functions in isolation and together: (a) pivot's distributional properties, (b) Source domain document's label constraints, and (c) Unlabeled target and source domain document's geometric properties. The experimental results presented that improved performance can be attained by optimizing the above three objective functions together than by optimizing individually each function. This verifies the importance of using domain-specific embedding learning for cross-domain opinion classification and get the regards as the finest performance of an individual objective function.

4.7 Case-based reasoning (CBR) techniques

Case-based reasoning utilized experience and predict the results of new problems.

Ohana et al. (2012)

Approach: Case-based reasoning (CBR), kNN, Euclidean distance, Stanford POS Tagger[29] and The General Inquirer (GI) lexicon, the Subjectivity Clues lexicon (Clues), SentiWordNet (SWN), the Moby lexicon and the MSOL lexicon (English Language)
Corpora: Hotel reviews dataset, IMDB dataset of film review, Amazon product review (Electronics, books, music, and apparel
Explanation: For cross-domain sentiment classification, proposed a new approach named as case-based reasoning. The case analysis is a feature vector based on document data, and the case explanation comprises all lexicons that made precise expectations during training. They considered the six different domain film reviews (IMDB), hotel reviews,[30] Amazon product review (Electronics, Books, music, and apparel) for sentiment classification. The experiment results are comparable to state-of-art.

[27] www.numpy.org.
[28] http://scikit-learn.org/.
[29] https://nlp.stanford.edu/software/tagger.shtml.
[30] http://www.tripadvisor.com/.

4.8 Graph-based techniques

A weighted graph is used for data representation in a Graph-based technique. In a weighted graph, nodes are data instance and weighted edge represent the relationship between those instances. In the graph-based approach, data is available in a manifold structure that is showing the instance's behavior and connection. If data is not in the form of manifold structure, we can use the similarity function to find the similarity between graph vertices. The good graph explains the suitable assessment of the similarity between the data instances. One of the most popular algorithms for the graph-based technique was label propagation developed by Zhu and Ghahramani (2002). The proposed algorithm learned from the labeled and unlabeled dataset for sentiment classification. Cross-domain sentiment classification based on graph-based techniques work is introduced by Ponomareva and Thelwall (2012a, b).

Ponomareva and Thelwall (2012a, b)

Approach: Optimisation problem (OPTIM), ranking algorithm (RANK), kNN, Graph-based approach, Support Vector Machines (SVMs) (LIBSVM library) and Amazon product review (English Language)
Corpora: Electronics, Books, DVDs, and Kitchen
Explanation: Compared the performance and effectiveness of two existing graph-based approaches named as a ranking algorithm (RANK) and an optimisation problem (OPTIM) for cross-domain opinion classification. The Optimisation problem (OPTIM) considered opinion as an optimization problem and ranking algorithm (RANK) utilized a ranking to allocate opinion scores. In order to find the document similarity, they analysed and performed various sentiment similarity measures such as feature-based and lexicon-based. In their experiments, they considered the amazon multi-domain dataset and compared the existing graph-based approach with each other and with other state-of-art approaches (*SCL* and *SFA*) for the cross-domain opinion classification. The experimental results showed comparable results. Later in the graph-based approach work is extended by Ponomareva and Thelwall (2013).

Ponomareva and Thelwall (2013)

Approach: Graph-based approach, modified label propagation (LP), semi-supervised learning (SSL), Cross-domain learning (CDL), linear-kernel Support vector machine (LIBSVM library), Class Mass Normalisation (CMN) and Amazon product review (English Language)
Corpora: Electronics, Books, DVD's and Kitchen
Explanation: Proposed a modified label propagation (LP) graph-based approach based on semi-supervised learning (SSL) and Cross-domain learning (CDL) algorithms. The authors observed the performance of graph-based label propagation (LP) along with its three variants (LPαβ, LP^{n}_{γ} LPγ) and its combination with class mass normalisation (CMN) on amazon multi-domain datasets in their experiments. Further in a graph-based approach: Zhu et al. (2013) to extract the labeled data with high precision from the target domain, utilized some emotion keywords and combined the labeled data of source domain and generated labeled data of target domain. After that performed the cross-domain sentiment classification and utilized label propagation (LP) algorithm, unlabeled and labeled data of the target domain. They used the amazon multi-domain dataset and the proposed approach achieves better performance.

4.9 Domain similarity and complexity techniques

Domain similarity is one of the approaches that can be used in domain adaptation to select the features from the source domain which are more similar to the target domain. To measure the domain similarity and variance in the complexity of the domains (Remus 2012) introduced the framework.

Remus (2012)

Approach: Domain similarity (pair-wise Jensen-Shannon (JS) divergence, unigram distributions, Kullback–Leibler (KL) divergence), Domain Complexity, Instant selection (ranked instances), Support Vector Machines (SVMs) with linear "kernel", LibSVM,[31] unigram, and bigram features and Multi-domain Sentiment Dataset v2.0[32] (English Language)
Corpora: Kitchen and housewares, health and personal care, electronics, books, music, apparel, DVD, toys and games, sports and outdoors and video
Explanation: In order to achieve high accuracy in cross-domain sentiment classification, the authors are tried to find the features from training data set that are similar in the test domain. This study utilized domain similarity, domain complexity and instant selection parameter in the proposed approach and achieved the comparative results in domain adaptation. For the experiment, they considered 10 different domains and rating information of reviews. They employ unigram distributions, Jensen-Shannon (JS) divergence and support vector machine with their cos parameter. Further, this work is extended by Ponomareva and Thelwall (2012a, b).

Ponomareva and Thelwall (2012a, b)

Approach: Domain similarity, Domain Complexity, parts-of-speech (POS), unigram distribution, linear regression, Support Vector Machines (SVMs) and Amazon Multi-domain Sentiment Dataset (English Language)
Corpora: Kitchen, Electronics, books, and DVD
Explanation: The authors utilized the domain similarity (divergence) and domain complexity (domain self-similarity) approaches. Analysed the performance loss of a cross-domain classifier (predict the average error of 1.5% and a maximum error of 3.4%).

4.10 Feature-based techniques

To improve the performance of cross-domain sentiment classification, feature-based techniques are used.

Xia et al. (2013)

Approach: {Feature ensemble plus sample selection (SS-FE), PCA-based sample selection (PCA-SS), Labeling adaptation, Instance adaptation (sample selection bias), part-of-speech (POS), Naive Bayes (NB) and Amazon Multi-domain Sentiment Dataset (English Language)

[31] http://www.csie.ntu.edu.tw/~cjlin/libsvm/.
[32] http://www.cs.jhu.edu/~mdredze/datasets/sentiment/.

Corpora: Kitchen, Electronics, books, and DVD
Explanation: Introduced a joint approach (that consider instance adaptation and labeling adaptation) named as feature ensemble plus sample selection (SS-FE). Feature ensemble model absorbs a new labeling function in a feature re-weighting manner and sample selection used principal component analysis as an aid to FE for instance adaptation. Experiments are performed on the amazon multi-domain dataset and outcomes indicated the effectiveness of SS-FE in both instance adaptation and labeling adaptation. Further:

Tsakalidis et al. (2014)

Approach: Text-Based Representation (TBR), Feature-Based Representation (FBR), Lexicon-Based Representation (LBR), Combined Representation (CR) (parts-of-speech (POS) using the Stanford POS Tagger + TBR, Ensemble Classifier (hybrid classifier (HC) and Lexicon-based (LC)), n-gram, TF-IDF and Twitter Test Datasets (English Langauge)
Corpora: Stanford Twitter Dataset Test Set (STS), Obama Healthcare Reform (HCR), and Obama-McCain Debate (OMD)
Explanation: Introduced an ensemble classifier that is trained on a domain and adapts without the need for additional ground truth on the test domain before classifying a document. To deal with the domain dependence problem in cross-domain sentiment classification, the ensemble algorithm is used on twitter datasets and results are comparable to state-of-art approaches.

Zhang et al. (2015)

Approach: Transferring the polarity of features (TPF), Kullback-Leiblern (KL) divergence, Cosine function, Linear classifier, Support vector machine (SVM), Rule-based classifier, bog-of-words, Co-occurrence matrix and Amazon Multi-domain Sentiment Dataset (English Langauge)
Corpora: Kitchen, Electronics, books, and DVD
Explanation: To address the two-issue polarity divergence and feature divergence in cross-domain sentiment classification, proposed a new approach named Transferring the Polarity of Features (TPF). In order to deal with these issues, the proposed approach selects the high priority independent features from the source and target domain and making the cluster of these high-polarity independent features. To transfer the polarity of the features, independent features work as a bridge between source and target domain. In their experiments, they utilized the amazon multi-domain dataset and the result showed the effectiveness of this approach.

4.11 Distance-based technique

In distance-based technique

Bisio et al. (2013)

Approach: {k-Nearest Neighbor (k-NN), bag-of-words, distance matric, distance-based predictive model WorldNet and Amazon Multi-domain Sentiment Dataset, TripAdvisor and English}

Corpora: {Kitchen, Electronics, Books, DVD, and hotel}
Explanation: Utilized the distance-based predictive model for opinion classification in the heterogeneous domain. The framework contained three steps. In the first step, they defined the distance metric and training corpus. In the second step, they classified the new review and with the help of a distance metric identify it in the training corpus. Lastly, according to a majority-rule strategy, an unlabeled review is tagged. In his experiments, utilized two publicly available datasets of reviews named amazon multi-domain datasets and hotel reviews from TripAdvisor and performance are evaluated in two different experiments.

4.12 Meta-classifier technique

The knowledge enhanced meta-classifier technique

Franco-salvador et al. (2015)

Approach: Knowledge-enhanced meta-learning (KE-Meta), Meta-learning (Stacked generalization)) bag-of-words classifier, word n-grams classifier (TF-IDF weighting and SVM classifier), lexical resource-based classifiers (SentiWordNet), vocabulary expansion-based classifier, Word Sense Disambiguation (WSD), Babelnet multilingual semantic network,[33] part of speech tagging and Amazon Multi-domain Sentiment Dataset (English Language)
Corpora: Kitchen, Electronics, Books, DVD
Explanation: For single and cross-domain sentiment classification, introduced new approach named Knowledge-enhanced meta-learning (KE-Meta) that combine different classifier such as bag-of-words classifier, word n-grams classifier, lexical resource-based classifiers, vocabulary expansion-based classifier, and Word Sense Disambiguation (WSD) based classifier. In the experiments, the proposed approach utilizes the amazon multi-domain dataset reviews and has confirmed to perform at par or better than state-of-art in single and cross-domain polarity classification. In order to generate features from vocabulary expansion and Word Sense Disambiguation, they utilized Babelnet multilingual semantic network. BabelNet (Navigli and Ponzetto 2012) is a multilingual encyclopedic dictionary or multilingual semantic network and represented similarly in WordNet.

In the next section, findings observed in a systematic survey are projected through discussion.

5 Discussion

The study explains all the tasks and sub-tasks of sentiment analysis with possible techniques and approaches. In order to perform sentiment analysis tasks, the most common approaches are machine learning, lexicon-based, and hybrid-based approaches. In this

[33] http://babelnet.org.

survey, different techniques, approaches, datasets, available tools, types of language, etc. for sentiment analysis tasks were presented in tabular form for better visualization and clear understanding. From the study, it can be stated that the machine learning approach is one of the most popular techniques followed by the lexicon-based approach, hybrid, deep learning, and other approaches used by the researchers in the field of sentiment analysis as represented in Fig. 17a. It is observed from the study, support vector machine is the most favourite technique followed by dictionary-based technique, Naïve Bayes, Maximum Entropy, Neural Network, Decision Tree, and other techniques as shown in Fig. 17b. This study focused and explained one of the sub-task of sentiment analysis named cross-domain opinion classification. Cross-domain opinion classification is one of the challenging research areas to work upon and it is observed from the survey that no perfect solution is available till now. Table 14, shows the pros and cons of the bassline techniques in cross-domain opinion classification.

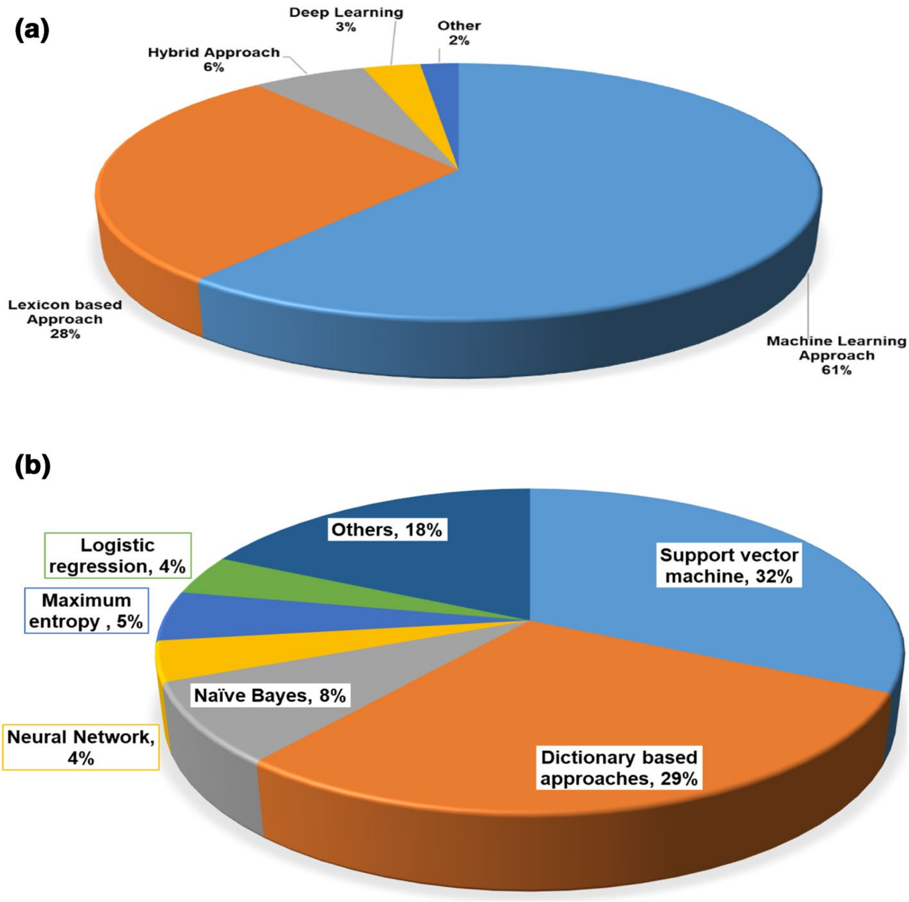

Fig. 17 **a** Percentage of articles according to the SA techniques, **b** percentage of articles according to the algorithmic approach

Table 14 Pros and cons of the most common baseline methods

Methodology	Pros	Cons
Structured Correspondence Learning (SCL)	The target domain's labeled dataset does not require for learning Easy to apply with different machine learning approaches	Highly dependent on the pivot features Too much expensive to train the classifier
Spectral Feature Alignment (SFA)	Find the co-relationship between domain-specific words and domain-independent words Easy to adapt multiple domains	Performance will goes down if the source and target domain's features are not correlated Expensive to annotate data for each new domain
Joint Sentiment-Topic (JST)	Identify the topics and sentiments concurrently Recognize and track benefits and shifts in sentiments and topics over time	Difficult to recognize the sentiment polarity of subtopics The joint Sentiment-Topic model is fully unsupervised
Active learning and deep learning approach	Take out high-level features from unlabeled data In order to obtain the output, active learning is capable to interactively query the information source	The Size of labeled data is more in the source domain High computational cost
Topic modeling	It does not require label information because of clustering techniques Significant and compact representation of documents	Mostly rely on both in- and out-of-domain datasets
Thesaurus-based techniques	Presented the comparable results in the single domain sentiment classification The target domain's labeled dataset does not require for learning	The result of thesaurus-based techniques highly dependent on the source and target domain
Graph-based approach	Multi-class classification can be handled The construction of a good graph gives better results	If graph is not good, the result may be unsatisfactory Graph-based approach dependents on weighting approaches
Domain similarity and complexity	Good features always give better results	Finding a similar instance from the source and target domain is a very hard and time-consuming process
Case-based reasoning (CBR) techniques	It captures the document's characteristics and document's statistics as a set of features Improve unsupervised opinion classification	Sometimes unpredictable behavior and output

The number of research articles considered from notable digital libraries and databases is explained in Fig. 18. All the publicly available datasets and toolkits along with resource links for sentiment analysis have been explained in this survey.

We briefly summaries more than hundred research articles using sentiment analysis attributes algorithms/Techniques, data scope and source, and language in Table 15.

6 Challenges and future directions

Various challenges and future scope in the area of sentiment analysis from the literature are identified few of which are as follows.

- **Availability of annotated corpora:** Due to the non-availability of annotated corpora, unsupervised and semi-supervised techniques have been adopted. However to provide a greater amount of performance it is necessary to have public availability of annotated corpora.
- **Pre-processing:** In the opinion mining system, data acquisition is often associated with unstructured, misspelled, and noise data from various sources. Per-processing includes parsing, POS tagging, word segmentation, tokenization, etc. which consume time for conversion into structured data. Hence there is scope for the development of tools or methods for automating the pre-processing stage.
- **Optimization:** Unlike traditional feature extraction methods (typically applicable for images), novel methods that can optimally associate text features and their sentiment should be explored for greater optimization during processing.

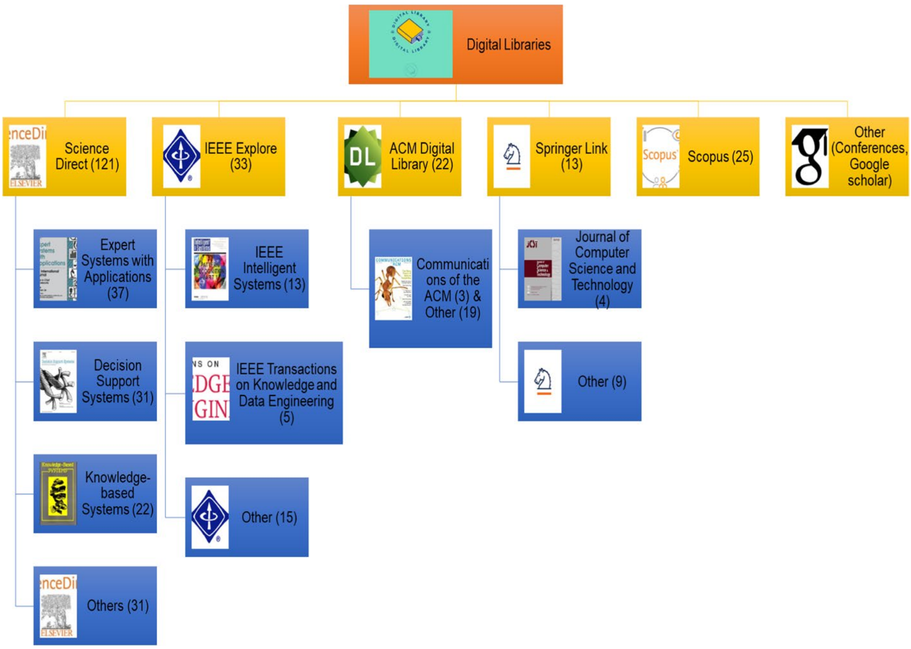

Fig. 18 Articles published in different digital libraries

Table 15 Summary of research articles in the field of sentiment analysis

References	Algorithms/techniques	Data scope and source	Language
Gruber (1995)	Knowledge-based, TF-IDF	Product review and General Inquirer	English
Nasukawa and Yi (2003)	Semantic analysis + syntactic parse + sentiment lexicon	Product review (Camera)	English
Hiroshi et al. (2004)	Machine learning and Lexicon based	Product review (Camera)	Japanese
Whitelaw et al. (2005)	Lexicon based approach, SMO learning approach, Bag of Words and Appraisal Group by Attitude, Orientation, and Force	Movie Reviews[a] and WordNet	English
Wilson et al. (2005)	Neutral-Polar Classification, dependency tree, BoosTexter AdaBoost.HM	Global Data and General-Inquirer	English
Mcdonald et al. (2007)	Linear classifiers, maximum Clique, MIRA learning algorithm	Product Reviews (Mp3 players, fitness equipment, car seats for children)	English
Benamara et al. (2007)	Adverb-adjective combinations (AACs), linguistic analysis	News articles and OASYS system	English
Zhou and Chaovalit (2008)	Ontology, Maximum-Likelihood, n-gram	Movie Review and www.imdb.com, General Inquirer	English
Wan (2008)	Semantic orientation value computation, Lexicon based approach	Product review (Chinese http://www.it168.com), and Google Translate, Yahoo Babel Fish, DictTrans	Chinese, English
Zhang (2008)	ν-support vector regression (ν –SVR), $\in$-support vector regression ($\in$-SVR), and radial-basis-kernel function (RBF)	Product Review (Electronics like canon and Sony product, books like engineering domain, video like PG-13 movie) and Amazon and CNET	English
Sindhwani and Melville (2008)	Support Vector Machines, POS tagging, feature-based approach	Micro-blogs (Twitter) and WordNet, (DAL) (Whissell 1989) Dictionary	English
Abbasi et al. (2008)	Entropy weighted genetic algorithm (EWGA) with SVM, Bootstrapping	Movie review and Web forum	English Arabic
Narayanan et al. (2009)	Linguistic analysis, Support Vector Machines, LIBSVM	Product review (Medicine, Audio systems, LCD TV, Cellphone, Automobile) and MPQA corpus[b]	English
Coussement and Poel (2009)	Random Forests, Support Vector Machines, Logistic Regression, Percentage Correctly Classified (PCC), eRFM and eRFM-EMO model, Area Under the receiving operating curve (AUC)	E-mail (newspaper company survey)	Brazil
Seki et al. (2009)	SVM^{light}, Conditional random fields (CRFs), Part of speech tagging	Product Reviews and MPQA Corpus, NTCIR-6 Opinion Corpus[c] (NII Test Collection for IR Systems)	Japanese English

Table 15 (continued)

References	Algorithms/techniques	Data scope and source	Language
Tan et al. (2009)	Adaptive-NB, Frequently Co-occurring Entropy (FCE), Naïve Bayes Transfer Classifier (NTBC), Chinese POS tool ICTCLAS	Product Review (Education, Stock, Computer) and Computer review: http://detail.zol.com.cn/, stock review: http://blog.sohu.com/stock/, Education review: http://blog.sohu.com/learning/.	Chinese
Zhan et al. (2009)	Stripping algorithm and a proposed new algorithm	Customer Review	English
Thelwall et al. (2010)	SVM (SMO), Multilayer Perceptron, JRip rule-based classifier, SentiStrength standard algorithm, AdaBoost	Myspace and SentiStrength	English
Lu et al. (2010)	Link analysis method, n-gram, POS tagging	Hotel review and http://www.ctrip.com/	Chinese
Mudambi and Schuff (2010)	Develop a new model, linear regression	Product review (MP3 player, PC video game, cell phone, digital camera, etc.) and amazon.com	English
Cambria et al. (2010)	Ontology approach, common sense, Knowledge-Base	Global data and SentiWordNet	English
Hassan and Radev (2010)	Random walks method, Markov random walk model	gold standard data set and General Inquirer lexicon, WordNet	English
Wei and Pal (2010)	Structural correspondence learning	Product review (Chinese http://www.it168.com), Product review (English)	English, Chinese
Li and Wu (2010)	SVM, K-means clustering	Sina sports forums[d] and Chinese word sets HowNet[e]	Chinese
Thelwall et al. (2011)	Lexicon based approach	Micro-blogs and SentiWordNet	English
Bai (2011)	Tabu search, Naïve Bayes, SVM, Maximum Entropy and enhanced Markov blanket model	MR and News review and IMDb, Google News (http://news.google.com)	English
Wang and Lee (2011)	Lexicon based approach, POS tagging, Sigmoid function	Blogs product review (digital camera) and Hownet http://www.keenage.com/download/sentiment.rar	Chinese
Jiang et al. (2011)	SVM^{Light} (http://svmlight.joachims.org/) Pointwise Mutual Information (PMI)	Micro-blogs (Twitter) and General Inquirer (GI) (http://www.wjh.harvard.edu/~inquirer/)	English
Ott et al. (2011)	Lexicon based approach, SVM^{light}, POS, n-gram (unigram and bigram)	Product Review (Amazon Mechanical Turk), Hotel review and Linguistic Inquiry and Word Count (LIWC)	English
Hu et al. (2011b)	Linear Regression	Product review (Book, DVD, Video)	English

Table 15 (continued)

References	Algorithms/techniques	Data scope and source	Language
Zhu et al. (2011)	Bootstrapping, Aspect-based opinion polling algorithm, NEUCSP tool (http://www.nlplab.com/chinese/source.htm)	Restaurant review and DianPing.com, Hownet	Chinese
Xu et al. (2011)	Bayesian networks, Conditional Random Fields (CRF)	Product review (Mobile phone) and Amazon online shopping site	English
Neviarouskaya et al. (2011)	Semantic analysis, lexicon-based approach	Develop SentiFul lexicon, SentiWordNet, GI	English
Hu et al. (2011a, b)	Discretionary review manipulation proxy	Book review and Amazon.com	English
Chen and Tseng (2011)	multiclass SVM, mature information quality (IQ)	Product review (Digital camera, mp3 players) and amazon.com	English
Zhai et al. (2011b)	SVM^{light} package, n-gram	Product review[f] (http://www.it168.com) hotel review[g] http://www.ctrip.com/ and tu-lexicon[h]	Chinese
Chen et al. (2011)	Semantic orientation indexes, term document matrix Back propagation neural network, TF-IDF, PMI	Movie review, Blogs (www.livejournal.com), product review (https://www.reviewcentre.com/)	English
Abbasi et al. (2011)	n-gram, WEKA's linear kernel SVM, Feature Relation Network (FRN)	Movie review (www.rottentomatoes.com), Automobile (www.edmunds.com), Product review Digital camera www.epinions.com	English
Ghose and Ipeirotis (2011)	Subjectivity levels, reviewer-level features, Random Forest-based classifiers, word-of-mouth	Product reviews (Digital camera, audio and video camera, DVS) and Amazon.com	English
Kang et al. (2012)	Improved NB, SVM, unigrams + bigrams, lexicon D1, D2, D3	Restaurant Review and Restaurant senti-lexicon (http://irlab.sejong.ac.kr/res-sentiwordnet/)	English
Yu et al. (2012)	Autoregressive Sentiment and Quality Aware (ARSQA) model, autoregressive Sentiment Aware (ARSA) model, S-PLSA and e -Support Vector regression with Radial Basis Function (RBF) kernels	Movie Review and IMDB websites (http://www.imdb.com)	English
Camp and Bosch (2012)	NB, LibSVM, NN, Jrip, KNN	Biographies (https://socialhistory.org/bwsa/) and Biographical Dictionary, Thesaurus + WSD	Dutch
Zhai et al. (2012)	Soft constrained Expectation maximization (SC-EM), naïve Bayesian EM	Product review (vacuums, cars, mattresses, home theatre, insurance) and WordNet	English

Table 15 (continued)

References	Algorithms/techniques	Data scope and source	Language
Liu et al. (2012)	Fuzzy domain sentiment ontology tree (FDSOT), Ontology learning (knowledge acquisition + machine learning)	Product reviews (Laptop) and 360buy.com	Chinese
Eirinaki et al. (2012)	High Adjective Count (HAC)	Product review	English
Lane et al. (2012)	SVM, ZeroR, Random, JRip, Bayesian networks, decision trees (J48), NB, radial basis function (RBF), K-NN	Newspapers and magazines	English
Thelwall et al. (2012)	Linear Regression, J48, Jrip, Decision Tree, Naïve Bayes, SMO-AdaBoost, SVM, SVR	BBC forums, Digg, Myspace, runners word, Twitter, and YouTube and SentiStrength 2	English
Balahur et al. (2012a, b)	Knowledge-Base (KB), Ontology Extension, k-mean	International Survey on Emotion Antecedents and Reactions (ISEAR) and SentiWordNet, ConceptNet, VerbOcean, EmotiNet	English
Neri et al. (2012)	Bayesian method, probabilistic classification, K-Means algorithm	Microtext, Facebook post (newscasts)	English
Tan et al. (2012)	Heuristic Rules, Class sequential rules (CSRs), Typed dependency tree	Movie review and SentiWordNet	English
Lin et al. (2012)	Joint sentiment-topic model, Latent Dirichlet allocation (LDA), Reverse-JST models, Bayesian Model	Movie reviews (MR),[i] multi-domain sentiment (MDS) (Book DVD Electronics Kitchen) datasets[j] and MPQA[k] and the appraisal lexicons[l]	English
Mohammad (2012)	Lexicon based approach (Dictionary based approach)	E-mail, book and Google Books Corpus, Fairy Tale Corpus (FTC), Corpus of English Novels (CEN) Roget Thesaurus[m]	English
Balahur et al. (2012a, b)	SVM (SMO), n-gram, Ontology expansion	International Survey on Emotion Antecedents and Reactions (ISEAR) and EmotiNet, VerbOcean WordNet Affect, LIWC	English
Racherla and Friske (2012)	Linear regression	Product review and Yelp.com	English
Huang and Yen (2013)	Regression analysis, rating, word count, rating × product type	Product review (MP3 player, PC video game, cell phone, digital camera, etc.) and amazon.com	English

Table 15 (continued)

References	Algorithms/techniques	Data scope and source	Language
Wang et al. (2013a, b)	Support vector machine, Statistical approach	Cell phone (English), Cell phone (Chinese), Hotel (Chinese)	English
Aloufi and Saddik (2013)	Support Vector Machine Classifier, Multinomial Naïve Bayes Classifier (MNB), Random Forest (RF), POS, BOW, and n-Gram	Twitter data of UEFA Champions League 2016/2017 and FIFA World Cup 2014 (MCR Lab website) http://www.mcrlab.net/datasets/	English
Wang et al. (2013a, b)	K-Nearest Neighbor, Maximum Entropy, Naive Bayes, Support Vector Machine, ensemble methods (Random Subspace, Boosting and Bagging), n-gram (Unigram and Bigram), TF-IDF, Decision Tree	Product reviews and forums (TV, Radio, Music, Movie, Lawyer, Laptop, Drug, Doctor, Camp, and Camera) and http://www.cs.indiana.edu/~mewhiteh/html/opinionmining.html	Chinese, English
Li and Li (2013)	Support Vector Machines, Naive Bayes, TF-IDF, POS-Tagger	Micro-blogs (Twitter), Brand (Google Microsoft Sony) Product (iPhone iPad Macbook)	English
Qiu et al. (2013a)	Symmetric Bayes–Nash Equilibrium, Twitter embedded prediction marker, social network-embedded prediction	Micro-blogs (Twitter, social network)	English
Martín-Valdivia et al. (2013)	Stacking algorithm, Lexicon based approach, SVM or NB, TF-IDF, Binary Term Occurrences, a Bayesian logistic regression, C4.5	Movie review (Spanish and English), and SentiWordNet, Spanish review corpus (http://www.lsi.us.es/~fermin/corpusCine.zip)	Spanish, English
Kontopoulos et al. (2013)	Lexicon based approach, Dictionary-based approach, ontology-based techniques	Micro-blogs and Collected hashtag tweets on smartphone http://goo.gl/UQvdx	English
Spina et al. (2013)	Neural Network, C4.5 Dec. Trees, CART Dec. Trees, Linear SVM, NB, filter keywords	Micro-blogs, Wikipedia and the searchable Web, company name disambiguation in Twitter, company's website, ODP	English
Li and Xu (2013)	Support Vector Machine, Support vector regression (SVR), Chinese POS tool ICTCLAS	Chinese micro-blogs and Weibo (web-based social network service in China)	Chinese
Rui et al. (2013)	Naive Bayesian classifier, word of mouth (WOM)	Movie sale review (http://www.boxofficemojo.com) Micro-blogs (Twitter)	English
Demirtas (2013)	SVM, NB, ME and Corpus-based and lexicon-based approach	Movie domain and Product Review (Books, DVDs, Kitchen and Electronics domain)	English, Turkish

Table 15 (continued)

References	Algorithms/techniques	Data scope and source	Language
Basari et al. (2013)	Support Vector Machine with Particle Swarm Optimization (SVM-PSO), TF-IDF, Confusion matrix, SVM, n-gram	Micro-blogs (Twitter), and Twitter data[n]	English
Mukherjee and Joshi (2013)	Ontology, POS Tagging	Product review, S/W, Automobile and SentiWordNet3.0, General Inquirer, ConceptNet (http://conceptnet5.media.mit.edu/)	English
Ott et al. (2013)	Support Vector Machine and n-gram	Product Review (Mechanical Turk crowdsourcing service) and Amazon	English
Ortigosa et al. (2013)	Support Vector Machine, J48 implementation of C4.5 decision-trees, Naïve Bayes	Facebook reviews, and Spanish Linguistic Inquiry and Word Count (LIWC)	Spanish
Yu et al. (2013a)	Naïve Bayes (NB)	Micro-blogs (blogs, twitter, forums, social media, etc.)	English
Kim et al. (2013)	Hierarchical aspect sentiment model (HASM), recursive Chinese Restaurant Process Bayesian nonparametric model	Product review (Camera, Digital SLRs) and http://uilab.kaist.ac.kr/research/WSDM11	English
Li and Tsai (2013)	Formal Concept Analysis (FCA) + Fuzzy FCA, Inverted Conformity Frequency (ICF), Uniformity (Uni), TF-IDF	Movie review, ebooks, Reuters and IMDB, Amazon's, economic news stories	English
Cruz et al. (2013)	Lexicon based approach, Random walk algorithm	Product review (car, headphone, and hotel)	English
Mostafa (2013)	Lexicon based approach	Random Tweets on (KLM, IBM, Nokia, T-mobile, DHL, etc.) and Hu and Liu online lexicon	English
Moghaddam and Ester (2013)	Factorized Latent Dirichlet Allocation (FLDA), EM algorithm	Product review (Accessories, Electronics, 1-5 star hotel) and Epinions, Amazon, TripAdvisor	English
Bagheri et al. (2013)	Modified Frequencies and Left and Right of the current word (FLR), PMI, A-Score Iterative Bootstrapping algorithm	Product review (Canon G3, DVD player, Nokia 6610) and Amazon.com and cnet.com	English
Ghiassi et al. (2013)	Dynamic Architecture for Artificial Neural Networks (DAN2), SVM, n-gram, TF-IDF	Micro-blogs (Twitter) and tweets of Justin Bieber	English
Hung and Lin (2013)	SVM, Lexicon based approach, WOM	Movie Review and IMDB, Revised SentiWordNet	English

Table 15 (continued)

References	Algorithms/techniques	Data scope and source	Language
Thelwall and Buckley (2013)	Lexicon based approach, Lexicon extension	BBC forums, Digg, Myspace, runners word, Twitter, and YouTube and SentiStrength	English
Li et al. (2014)	Lexicon based approach, SenticNet, BOW, Vector space model, support vector machines	Stock exchange, news archive, and FINET9 Loughran–McDonald financial sentiment dictionary, Harvard psychological dictionary	English
Cambria et al. (2014)	Lexicon based approach, Semantic Parsing, group average agglomerative clustering (GAAC), Common-Sense Knowledge Base	National health service (NHS), Global domain and SenticNet, WordNet	English
Poria et al. (2014b)	Common-sense reasoning, fuzzy c-means clustering, SVM	ISEAR dataset and EmoSenticSpace°, SenticNet, WordNet-Affect	English
Weichselbraun et al. (2014)	Lexicon based approach, Knowledge-Base	Product review (amazon), movie review (IMDb) and ConceptNet and WordNet	English
Banerjee and Chua (2014)	Variance inflation factors, logistic regression, Lexicon based approach	Hotel review and Linguistic Inquiry and Word Count (LIWC)	English
Poria et al. (2014a)	Linguistic rules, sentic computing, Vector Space Model, extreme learning machine	Global data and SenticNet framework, AffectiveSpace	English
Tang et al. (2014)	A neural network, Sentiment-Specific Phrase Embedding	Micro-blogs (Twitter) and Urban Dictionary, sentiment lexicon (TS-Lex)	English
Kanayama and Nasukawa (2014)	Context coherency, Lexicon based approach	Movie and Product review	Japanese
Khan et al. (2014)	Lexicon based approach, SentiWordNet Classifier, Improved Polarity Classifier, Enhanced Emoticon Classifier	Micro-blogs (Tweets on Imran Khan, Nawaz Sharif, Dhoni, Tom Cruise, Pakistan, America and SentiWordNet3.0	English
Kang and Park (2014)	Lexicon based approach, multicriteria decision making (MCDM) approach, VIKOR (in Serbian: ViseKriterijumsa Optimizacija I Kompromisno Resenje)	Mobile reviews and SentiWordNet	English
Lau et al. (2014)	Bipartite graph, Semi-supervised Lexical Regularized Least Squares (SS + LEX + RLS) classification, Transductive SVM	Micro-blogs (Lotus and political candidate) and IBM Lotus brand	English

Table 15 (continued)

References	Algorithms/techniques	Data scope and source	Language
Mukherjee and Joshi (2014)	Phrase annotated Author specific sentiment Ontology Tree (PASOT), bag-of-words unigram, L2-regularized	Movie Review and IMDb, WordNet.	English
Vinodhini and Chandrasekaran (2014)	Bagging, Bayesian boosting based model, logistic regression, support vector machine, n-gram, PCA and PC1	Product Review (digital camera), and Amazon (http://www.amazonre views.com)	English
Bell et al. (2014)	Lexicon based approach	Micro-blogs and ConceptNet, WordNet, and JMDic	English
Rill et al. (2014)	Concept-level sentiment analysis	Micro-blogs (political topics) and SentiWordNet3.0	German
Popescu and Strapparava (2014)	Lexicon based approach, statistical approach	Multi-domain (socio-political domain, sport) and Google N-gram corpus, WordNet-Affect	English
Wu and Tsai (2014)	Common sense knowledge base, LIB-SVM	Movie Review and Product Review and ConceptNet, SenticNet, ANEW	English
Costa et al. (2014)	Random Forest and Radial Basis Function (RBF) kernel to allow the SVM model	Location-Based Social Networks (LBSN) and Aponta-dor	Brazil Portuguese
Montejo-Raez et al. (2014)	SVM, TF.IDF-cosine approach, Lexicon based approach	Micro-blogs and SenticNet 3, WeFeelFine (http://wefeelfine.org)	English Spanish
Justo et al. (2014)	Classical Naive Bayes classifier, a rule-based classifier	Statistical Cues, Mechanical Turk Cues and Linguistic Inquiry and Word Count (LIWC), SenticNet 3	English
Hai et al. (2014)	Intrinsic and extrinsic domain relevance, TF-IDF	Product review (Cellphone), Hotel	Chinese
Fusilier et al. (2015)	Modified PU-learning, Naïve Bayes	Product review, Hotel Review	English
Nassirtoussi et al. (2015)	Synchronous Targeted Feature Reduction (STFR), SVM, TF-IDF	News headlines, Forex Rate and SentimentWordNet	English
Cambria et al. (2016)	Linear discriminant analysis (LDA), AffectNet graph, Semantic Features	Blitzer Dataset, Movie Review Dataset (Pang and Lee 2005)	English
Poria et al. (2016a)	7-layer deep convolutional neural network, Word embeddings	Laptop and Restaurant, Amazon embeddings (http://sentic.net/AmazonWE.zip), Product Domain	English
Tartir and Abdul-Nabi (2017)	Ontology approach, Arabic Sentiment Ontology (ASO)	Arabic database (http://en.mo3jam.com/), Microblogs Twitter on Ro'ya TV[p], Jamalon[q], Khaberni[r]	Arabic

Table 15 (continued)

References	Algorithms/techniques	Data scope and source	Language
Chan and Chong (2017)	Likelihood ratio (LR), Pointwise mutual information (PMI), radial basis function (RBF) kernel, meta-decision tree (MDT), C-support vector classification (C-SVC)	Movie data set (Pang et al. 2002) and Online Financial Text Stream (financial news on Hong Kong financial website called Finet	English, Chinese
Araque et al. (2017)	Linear machine learning algorithm, word embeddings model,	Movie reviews domain, microblogging	English
Satapathy et al. (2017)	Lexicon-Based Approach, phonetic code matching, normalize OOV words, Ratcliff pattern matchning algorithm	Microtext (Twitter), 4000 tweets (randomly selected) SenticNet, Sentic API	English
Harakawa et al. (2017)	Weighted signed network, modularity-based measure, Web video retrieval	YouTube (https://www.youtube.com/), YouTube-8 M	English
Li et al. (2017)	Word embedding (GloVe), Stanford Sentiment Treebank (SST), convolution neural network	MovieReview, SenticNet, multi-perspective question answering (MPQA) corpus, NRC, Urban dictionary and Youdao	Urban
Virmani et al. (2017)	Bag-of-words, Lexical Boms Dictionary, BOWN (bag of words and n-gram), Synonym replacement (WSR), cross-domain analyzer (CDA), BOMEST	Product reviews (baby products, beauty products, health products, electronics products) form Amazon http://jmcauley.ucsd.edu/data/amazon/	English
Marcacini et al. (2018)	Aspect-Based Sentiment Analysis (ABSA), Cross-Domain Aspect Label Propagation through Heterogeneous Networks, a label propagation algorithm, transductive learning process	Products and Services reviews (Digital camera, Cellular phone, MP3 Player, DVD Player, Laptop, Restaurant)	English
Abdelwahab and Elmaghraby (2018)	Markov Chain based, recursive neural networks (Long Short Term Memory networks and Gated Recurrent Unit (GRU)), TF-IDF, rule-based classifier	Kitchen Product Reviews	English
Chen et al. (2018)	weakly supervised multimodal deep learning (WS-MDL), convolutional neural networks, Expectation–Maximization algorithm	Microblogs (Sina Weibo), Tweets	English

Table 15 (continued)

References	Algorithms/techniques	Data scope and source	Language
Shuang et al. (2018)	Sentiment Information Extractor (SIE), Sentiment Information Collector (SIC), Neural Network, Bi-directional Long Short Term Memory	Chinese Sine Microblogs (http://weibo.com), Amazon Product review in English (Stanford Network Analysis Project (Mcauley and Leskovec 2013) (SNAP): https://snap.stanford.edu/data/web-amazon.html)	English, Chinese
Dey et al. (2018)	Senti-N-Gram, rule-based approach, Lexicon based approach, bigram, and trigram	Product Reviews (Phone, music, computer, car, Hotels, books, etc.) http://www.epinions.com/	English
Wang et al. (2018b)	Stacked residual Long Short-Term Memory model, conventional deep NN-based methods	VADER dataset (digital product reviews, social media texts, news articles, movie reviews), Stanford sentiment treebank (SST), VADER corpora, Chinese valence-arousal texts (CVAT)	English, Chinese
Ma et al. (2018)	Sentic long short-term memory (LSTM), common sense knowledge	SentiHood (Yahoo! Answers with location), and subset of Semeval 2015 dataset	English
Vilares et al. (2018)	Statistical machine translation tool, common sense knowledge	SenticNet, BabelSenticNet, WordNet	Multilingual
Zhao et al. (2018)	Convolutional Neural Network based on Weakly-supervised Deep Embedding (CNN-WDE), Long Short-Term Memory based on Weakly-supervised Deep Embedding (LSTM-WDE)	Product review from Amazon (Laptop, Cell phones, and digital camera) (McAuley et al. 2015) http://cseweb.ucsd.edu/~jmcauley/	English
Fu et al. (2018)	Long short-term memory networks (LSTMs), word embeddings, lexicon-enhanced LSTM model	5 different datasets (IMDB, Yelp2013, MR, NB4000, Book4000) First three in English dataset and rest 2 in Chinese dataset.	English, Chinese
Fang et al. (2018)	Multi-Strategy Sentiment analysis of Support vector machine and Naïve Bayes, semantic fuzziness	Consumer reviews on hotel (http://www.searchforum.org.cn/tansongbo/senti_corpus.jsp)	Chinese
Cambria et al. (2018)	Bi-Long short-term memory (biLSTM), word embedding	2-Billion-word ukWaC, Blitzer Dataset	English
Abdi et al. (2019)	Sentiment shifter rules, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), RNN-LSTM, for sentiment analysis (RNSA)	Movie Review (MR) Dataset, Document Understanding Conferences (DUC) datasets (http://duc.nist.gov)	English

Table 15 (continued)

References	Algorithms/techniques	Data scope and source	Language
Manshu and Bing (2019)	Hierarchical attention network with prior knowledge information (HANP), 3-layer Convolutional Neural Network (CNN), bidirectional LSTM	Amazon public datasets, Kitchen, Video, Electronics, Books, and DVD	English
Feizollah et al. (2019)	Recurrent neural networks (RNN), long short-term memory (LSTM), convolutional neural networks (CNN), Word2vec feature extraction, MD5 value	Microblog (Twitter keyword halal cosmetics and halal tourism), Yelp (hotel and restaurant reviews), Amazon (product reviews), IMDB (movie reviews), eRezeki (digital worker perceptions)	English, Malay
Fu et al. (2019)	Long and Short Time Memory neural network (LSTM), TextCNN, stochastic gradient descent (SGD)	Sina Weibo (https://www.weibo.com/), Baidu Post Bar (https://tieba.baidu.com/)	Chinese
Ghulam et al. (2019)	Long Short-term Memory (LSTM), Recurrent Neural Nework (RNN), Word embedding	Roman Urdu Corps	Urdu
Satapathy et al. (2019a)	Sentic API, convolutional neural network (CNN) with LSTM, long short-term memory (LSTM), Attentive LSTM, gated recurrent units (GRU), seq 2seq model	Microtext Lexicon, Carnegie Mellon Pronouncing Dictionary (CMUdict), NUS SMS Corpus, Normalized Tweets	English
Rida-e-fatima et al. (2019)	Word Embeddings using Word2vec model, K-nearest neighbhor, ‘Bi-directional Refined Dual Attention Model’’ (B-RDAM)	Product review (Restaurant, Laptop)	English
Majumder et al. (2019)	Attention network, neural tensor network, Gated recurrent units	Eye-movement data of seven readers (994 samples)	English
Zhang et al. (2019)	Generative Adversarial Network, Seq 2Seq based neural network, Cosine Similarity	Amazon and Yelp dataset	English
Satapathy et al. (2019b)	Binary classifier, OOV words, Concept parser, phonetic encoding, International Phonetic Alphabet for normalization	Microtext, NUS SMS Corpus, SenticNet, Sentic API, PhonSenticNet	English
Zhao et al. (2019)	Convolutional Layer, Capsule Layer, negative agreement score (NAS) Kernel Density Estimation	Regular label scale dataset (RCV1), large label scale dataset (EUR-Lex), CNN baseline	English

Table 15 (continued)

[a]http://www.cs.cornell.edu/people/pabo/movie-review-data/
[b]http://www.cs.pitt.edu/mpqa
[c]http://research.nii.ac.jp/ntcir/ntcir-ws6/opinion/index-en.html
[d]http://bbs.sports.sina.com.cn/treeforum/App/list.php?bbsid=33&subid=0
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[m]http://thesaurus.com/Roget-alpha-index.html
[n]http://www.stanford.edu/~alecmgo/cs224n/trainingandtestdata.zip
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- Micro-blog based opinions (limited in words), often associated with sarcasm and irony are language and culture dependent. Fewer explorations have been carried out in analyzing such statements, thereby demanding cognitive intelligence intervention for rescue. Similar is the case with phonetic multi-lingual sentiment classification.
- Associated areas such as review spam detection, review usefulness, and opinion summarization are also significantly influencing the overall sentiment of a given opinion, hence requires attention for improving the efficiency of opinion mining.
- Cross-domain sentiment analysis is another neish area that has the potential to associate stronger sentiment by understanding various behavioral perspectives of the user.
  - As per the review indicated in this paper, very limited research in the area of cross-domain sentiment analysis is discovered.
  - Fewer literature is observed in the area of Social Media Code Mixed Texts. When it comes to Non-English based, no research is found. Indicating there is a dire need for this research.
  - Since the creation of a corpus is a cost-oriented approach, transfer learning can be another methodology that can be used for performing sentiment classification.
- Deep learning is another methodology that is often utilized by industrial researchers for computational advantage to overcome flaws in traditional methods like lexical, feature extraction, and classification.

7 Conclusion

In the field of text mining and natural language processing, opinion analysis is one of the interesting and active research areas to work upon. This article covers research articles/papers/reports of sentiment analysis published in different journals, conferences, and magazines from last more than one decade. This study covers different levels of sentiment analysis and different tasks of sentiment analysis such as subjectivity classification, degree of usefulness measurement, opinion summarization, sentiment lexicon creation, aspect selection, spam review detection, and opinion classification. Opinion classification is categorized into some sub-tasks such as cross-domain opinion classification, cross-lingual, multi-lingual opinion classification, polarity extraction, etc. All the tasks and sub-tasks of sentiment analysis are reviewed in some aspects like, different approaches, techniques, and methodologies employed, datasets exploited, lexicon and corpus utilized and type of languages used by the researcher. In this survey, we saw the different intelligent techniques apart from Neural network, Maximum entropy, Naïve Bayes, Support vector machine, lexicon-based approach which has been used in sentiment analysis for different tasks such as for better feature extraction utilized the conditional random field theory, for finding the common opinion words rule miner techniques is used. This literature survey emphasis the methodologies or approaches, publicly available pre-processing toolkits, review datasets/source, sentiment lexicons, and type of language used by the author for better visualization in the field of sentiment analysis. Along with sentiment analysis, we have also discussed cross-domain opinion classification in detail as this is one of the challenging and interesting research areas to work upon.

We summarized more than a hundred different research articles along with some open issues and challenges in the field of sentiment analysis that will help the new researchers. It is observed from the survey analysis that there is no perfect solution available in cross-domain opinion classification.

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