Knowledge-Based Systems 222 (2021) 107018

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Fuzzy logic applied to opinion mining: A review

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A R T I C L E I N F O

Article history:
Received 8 November 2020
Received in revised form 28 February 2021
Accepted 2 April 2021
Available online 5 April 2021

Keywords:
Sentiment analysis
Fuzzy logic
Multicriteria decision making
Opinion mining

A B S T R A C T

The advent of Web 2.0 and its continuous growth has yielded enormous amounts of freely available user-generated information. Within this information, it is easy to find subjective texts, especially on social networks and eCommerce platforms that contain valuable information about users. Consequently, the field of opinion mining has attracted considerable interest over the last decade. Many new research articles are published every day, in which different artificial intelligence techniques (e.g., neural networks, fuzzy logic, clustering algorithms, and evolving computing) are applied to various tasks and applications related to opinion mining.

Given this context, this survey presents a rigorous review of the different applications of fuzzy logic in opinion mining. The review portrays different uses of fuzzy logic and summarizes over one hundred and twenty articles published in the past decade regarding tasks and applications of opinion mining. This study is organized around three primary tasks, feature processing, review classification and emotions and also pays special attention to sentiment analysis applications whose core technique uses fuzzy logic to achieve the stated goals.

1. Introduction

In the past few years, applications related to sentiment analysis, also called opinion mining, have been gaining much influence in the field of artificial intelligence (AI). The development of new technologies and applications, especially on the Internet, such as e-Commerce platforms and social networks, makes it possible that users can spread their opinions everywhere. This new content source provides us with valuable information that is currently being exploited by many researchers with the aim of improving classical applications such as recommender systems and decision support systems. For that reason, the number of articles published related to this research area is growing every day. Likewise, the number of publications found in the area of fuzzy logic has steadily grown over the last decades [1].

A vast number of new studies in the field of opinion mining are published every year. Different new contributions can be found regarding to the use of generation, adaptation or use of new sentimental lexicons [2–6], the application of classical machine learning algorithms such as support vector machines [7], naive Bayes [8], regression methods [9], decision trees [10], clustering [11] or even, ensemble classifiers and genetic algorithms [12] or transfer learning [13]. And particularly, the application of deep learning is gaining a lot of interest [14]. Thus, the reader can find many recent studies applying, for example, long short-term memory (LSTM) models [15,16], convolutional neural networks (CNN) [16,17], attention-based deep models [18–24], lexicon integrated CNN–LSTM models [25,26], recurrent convolutional neural networks [27], among other related models.

Likewise, many broad reviews have been conducted in the field of sentiment analysis [28–31], whereas others have been focused on the influence of different techniques, such as deep learning [32,33] or information fusion [34,35], or specific tasks such as feature detection [36] or subjectivity detection [37], and even about tools [38] or languages different from English [39]. In Table 1, the reader can see a summary of some of the most recent reviews in opinion mining, as well as the different aspects that are analyzed. Nonetheless, despite the growing interest in fuzzy logic applied to opinion mining, a systematic overview of the solutions proposed in the scientific literature is lacking. To the best of our knowledge, this is the only study that has focused on this specific topic. Inspired by these other reviews (see Table 1), the present paper analyzes similar aspects such as feature detection, classification techniques or applications, but emphasizing the contributions made by fuzzy logic.

Hence, the goal of this paper is to systematize the existing knowledge regarding the different applications of fuzzy logic in the field of opinion mining through a literature review. This research focuses primarily on the wide variety of tasks that can be performed in the field of sentiment analysis as well as other applications that clearly depend on sentiment analysis tasks to achieve their goals. In all these cases, to meet the requirements

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https://doi.org/10.1016/j.knosys.2021.107018
0950-7051/

Table 1
Summary of reviews on sentiment analysis.

References	Analyzed aspects	Novelty/Main focus
[28,31]	Feature and aspect extraction, classification techniques and applications	General overview
[32]	Analysis level (document, sentence...), aspect extraction, sarcasm, emotion, etc.	Deep learning
[33]	Deep-learning based-rating prediction models and recommender systems	Deep learning and recommender systems
[34]	Feature extraction, classification techniques, related applications	Ranking products by Information fusion
[35]	Fusion of data sources, resources and techniques	information fusion
[36]	Extraction techniques: supervised, semi-supervised and unsupervised	Aspects extraction methods
[37]	Techniques (syntactic, semantic, multimodal), new domains and benchmarks	Subjectivity detection
[38]	Comparative experiments	Tools
[39]	Monolingual and bilingual: Features and classification (deep learning, machine learning, hybrid and corpus)	Arabic language

of this review, fuzzy logic must be the main technique applied to perform an essential opinion mining-related task, phase or application; however, other techniques can also be applied as part of the entire process or application. Thus, for example, this article does not cover topics related to natural language processing (NLP), which may be applied in opinion mining as in [40], despite the close relationship between such techniques and fuzzy logic techniques.

This review was carried out using a systematic approach that gathered and filtered the data sample. First, searches were performed on the most important online research databases, such as WebOfSciences and Scopus, to identify the most recent studies. The query used to collect the necessary information included the following keywords: "fuzzy logic", "fuzzy sets" (this approach also covered extensions such as "interval-valued fuzzy sets" (IVFSs), "pythagorean fuzzy sets" (PFSs), "type-2 fuzzy sets" (T2FSs), "interval type-2 fuzzy sets" (IT2FSs), "neutrosophic fuzzy sets" (NFSs), "hesitant fuzzy sets" (HFSs), and so on), "choquet integral, "sentiment analysis", "hate", "affective computing", "opinion mining", "microblogging", "subjectivity", "polarity", "emotion", "feelings", "irony", "sarcasm", "cyberbullying", "twitter", "rating detection", "ewom" (electronic word-of-mouth), "aspect detection", "feature detection", "review-based", "opinion-based" and "aspect-based". After the search process was complete, over 2000 documents had been collected. This initial list was manually revised to filter out papers that were not clearly aligned to applications and tasks related to opinion mining and solved by fuzzy logic-based strategies. Most the omitted papers were found by browsing keywords, titles and abstracts. Eventually, 197 papers were found that had been thoroughly revised. After that process, approximately 120 papers were obtained and are described in this review, which synthesizes the most important aspects of the interactions between both fields in each paper. Due to the fact that different fuzzy logic-based techniques have been applied in the same study or the same but in different phases, several studies could appear in different subsections of this review.

The current review is conducted in three primary dimensions: feature-related tasks, classification and emotions; in addition, a fourth dimension is included: sentiment analysis applications. Feature extraction and selection is the key to developing many tasks and applications, especially those related to aspect-based sentiment analysis (ABSA) [41]. The classification mechanisms are divided into semantic and machine learning-based approaches. Semantic approaches use ontologies and dictionaries to represent different steps of the sentiment classification process in a fuzzy manner. The articles related to machine learning techniques focus primarily on supervised algorithms, but some apply unsupervised algorithms. The nature of the applications found is broad; however, the primary categories are related to the stock market, opinion retrieval, summarization and multicriteria decision making (MCDM). Emotion analysis is closely related to sentiment analysis, but such topics could also be grouped into a broader field such as affective computing [42]. In this study, the selected articles utilize fuzzy logic and emotions to rate opinions. The remainder of this review is structured as follows: In Section 2, some preliminaries about sentiment analysis and fuzzy logic are discussed. Section 3 provides comments on the content of some papers related to feature detection and characterization. Section 4 focuses on the different techniques used for sentiment classification and polarity rating calculation. Section 5 covers the articles on emotions applied to opinion ratings, and various applications that combine fuzzy logic with sentiment analysis are described in Section 6. Section 7 discusses some open challenges and finally, Section 8 concludes the paper.

2. Preliminaries

2.1. Opinion mining

Sentiment analysis, also called opinion mining, is a recent research field mainly focused on discovering people's sentiments, emotions and/or feelings on a product/service from texts. In a simple way, an opinion might be defined as a positive or negative sentiment or emotion on an entity or aspect of said entity. It is mathematically defined by Liu [43] as a 5-tuple (e_j; a_{jk}; so_{ijkl}; h_i; t_l) where e_j represents a target entity and a_{jk} is the kth aspect/feature of that entity e_j. so_{ijkl} is the sentiment assessment of the opinion according to the opinion holder h_i on an aspect/feature a_{jk} from entity e_j at time t_l. h_i is the person conveying the opinion, also called opinion holder, and t_l is the moment when the opinion was conveyed.

Opinion mining can be studied from different points of view, one of which is the level of analysis. Three main levels can be described depending on the target: (i) the document level, (ii) the sentence level and (iii) the entity/feature/aspect level [44].

2.1.1. Tasks, phases and applications

Several authors describe the various tasks that can be associated with the field of opinion mining using different names. For instance, Liu and Zhang enumerated the following tasks in [45]:

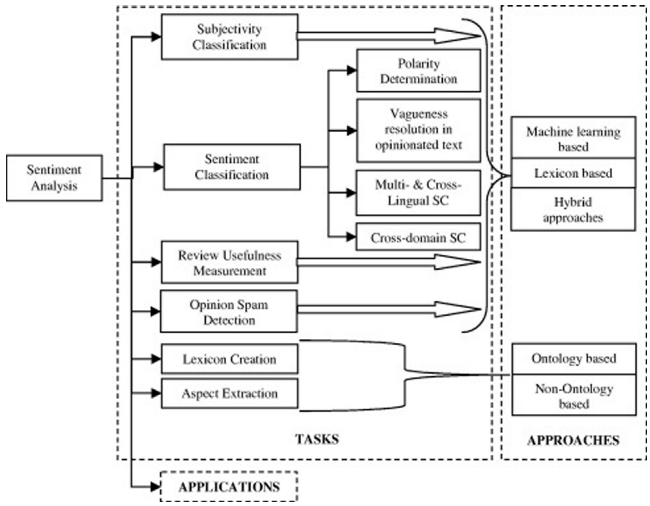

Fig. 1. Tasks in opinion mining [28].

- Sentiment analysis is a subarea of text mining responsible for examining and recognizing sentiments in opinions.
- Opinion extraction consists of searching on the Internet to collect texts that can be considered opinions.
- Sentiment mining primarily consists of detecting content that is sufficiently subjective to be considered opinion. Subsequently, these opinions must be classified into three categories: positive, negative and neutral.
- Subjectivity analysis has the goal of identifying, classifying, and collecting subjective sentences from user reviews.
- Affect or emotion analysis is not solely positive or negative; opinions can contain emotions such as happiness or rage that should be detected.
- Review mining extracts features from opinions with the goal of summarizing the subjective content expressed in product reviews.

In [28], Ravi et al. synthesized all the articles up to that date on opinion mining, paying attention to the different known tasks, applications and approaches. Apart from the above categories but using different names, they added other new subtasks and grouped the tasks included in opinion mining into the following categories: subjectivity and sentiment classification, review usefulness metrics, opinion spam detection, lexicon creation and aspect extraction (see Fig. 1).

When performing most of these tasks, various techniques can be applied. These techniques focus primarily on machine learning and semantic approaches—that is, the use of external knowledge resources such as ontologies or thesauruses. As shown in Fig. 2, Hemmatian et al. synthesized most of the possible techniques applicable to different tasks, but paid special attention to sentiment classification [29].

2.2. Fuzzy sets and their extensions

Solving real-world problems requires dealing with many uncertain factors. According to the varying nature of the uncertainty, different types such as randomness, fuzziness, indistinguishability and incompleteness can be found. To cope with this uncertainty, different techniques, such as fuzzy logic, have been proposed in the AI field.

In essence, fuzzy logic allows imprecise information from the real world to be processed. Not only does fuzzy logic allow for a more realistic representation of real-world information, but it also does so using a simple approach. In general, fuzzy logic-based models require fewer rules and variables than do other model types.

Fuzzy set theory is based on the idea that in the real world, things are typically allowed to be a matter of degree. Thus, Zadeh introduced the concept of a fuzzy set in 1965 [46], which is a mechanism to represent the attribution of membership degrees to different elements found in real-world applications. Mathematically, different definitions can be found, for instance, a fuzzy set (or type-1 fuzzy set (T1FS)) A on X is a mapping $A : X \longrightarrow [0, 1]$, where A(x) refers to the membership degree of element x to fuzzy set A.

Fuzzy set theory has some limitations, especially when coping with different information sources. Therefore, several extensions have been proposed in the literature, such as IVFSs, IVAFSs, PFSs, T2FSs, IT2FSs, NFSs, HFSs, among many others. The relationships between the different types of fuzzy sets are described in detail in [1,47], and a summary is shown in Fig. 3.

3. Features: extraction and detection

As mentioned above, various analysis levels (document, sentence and aspect/feature) can be found in opinion mining. The feature level is a fine-grained model whose goal is to determine the user's intention regarding a specific aspect of any product, service, or entity. Aspects can be classified as explicit when clearly expressed in the text, or implicit, when inference is necessary to determine what is being referring to. Several different techniques have been utilized to extract and detect features, including fuzzy logic.

For instance, [48] utilized fuzzy logic to construct a fuzzy aspect-based opinion classification system applied to TripAdvisor data. In this study, fuzzy logic is used in 2 steps of the algorithm to extract aspects and classify opinions. To classify the detected aspects, both implicit and explicit, the authors used a fuzzy rule-based algorithm called the fuzzy unordered rule induction algorithm (FURIA) [49]. The model processes sentences by extracting the most frequent words tagged as nouns by part-of-speech (POS) tagging along with their related coreferential words. These words and coreferences are enlarged using WordNet's synonyms. The most frequent aspects are selected according to the TF–IDF formula [50]; then, the FURIA algorithm is applied to design a set of rules to associate each word's sentence to a feature. Finally, all the sentences from a collection are extracted and assigned a feature if possible; sentences for which a feature cannot be assigned are discarded. The remaining sentences are considered to be opinion sentences.

Bing and Chan extracted the important words from a Twitter collection using the TF–IDF formula [51]. The extracted terms are then associated both with sentiments from SentiWordNet [52] and with a fuzzy set consisting of 5 predefined sets [Positive+, Positive, Neutral, Negative, Negative−] whose membership degrees are based on a Gaussian distribution. The tweets are then represented as vectors that include the fuzzy information from all the words forming each tweet. The entire collection is an array treated as a multilevel matrix and summarized using a simplification/reduction process. The result is a set of vectors that represent different multilayers of features from the collections and each one is associated with the 5 previous sentiment categories. This process yields a set of fuzzy rules whose importance weight is measured via the chi-square test to calculate the resemblances between features.

An application to analyze Twitter that includes different functionalities was proposed in [53]. The main topics people are discussing are detected by the fuzzy fingerprint method [54], and the number of tweets per topic is calculated by a fuzzy uke word

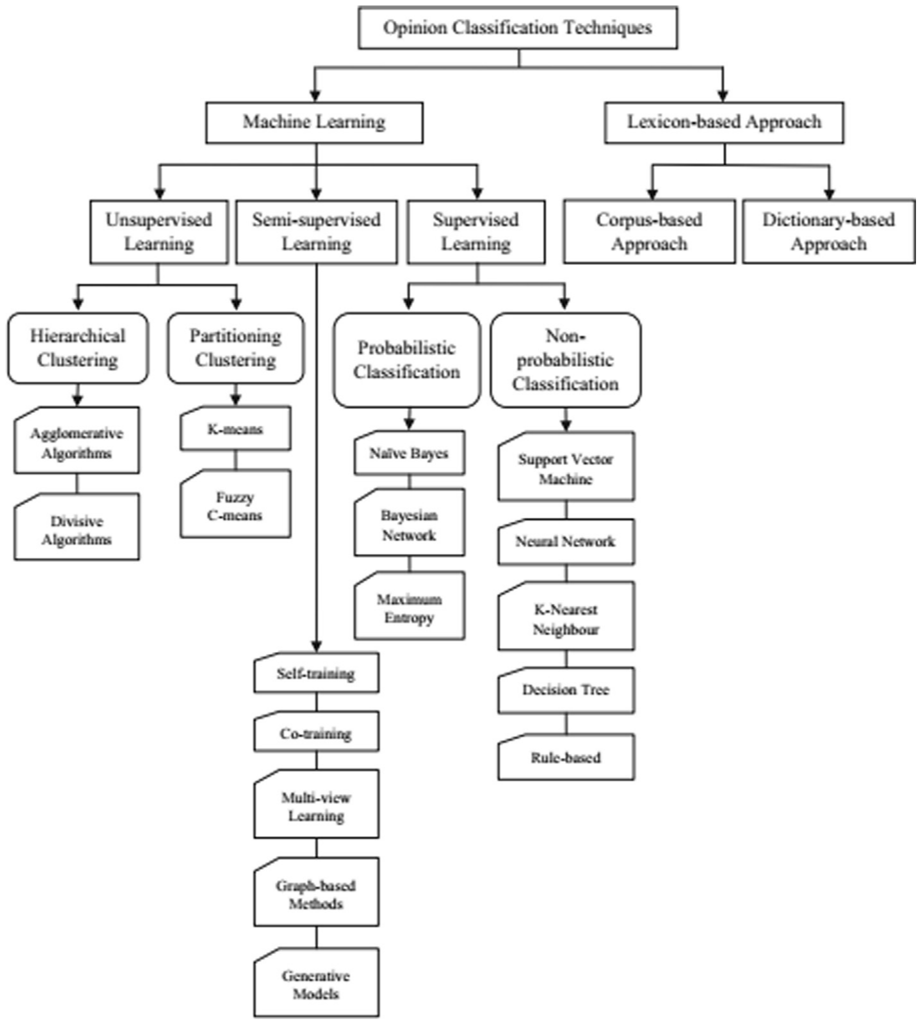

Fig. 2. Techniques applied to opinion classification [29].

similarity algorithm that compares the similarity of the hashtags related to each topic. Based on the acquired topics, sentiment classification techniques are then applied to analyze the tweets for each topic.

In [55], a fuzzy c-means algorithm is used as part of the process to determine the aspects of the products to be ranked. First, it applies a preprocessing step that detects nouns as explicit features and, then applies a cooccurrence association rule-mining process to infer the implicit aspects. These aspects are grouped into different clusters by a fuzzy c-means algorithm. Opinion words (adjectives) and aspects are associated by an undirected graph, and a graph-based co-ranking algorithm is used to select the features for each product. The opinion words are classified into five categories [very good, good, medium, poor and very poor] represented by 5 triangular fuzzy numbers (TFNs). A fuzzy decision matrix is generated for each feature that includes the fuzzy values of the opinion words linked to the different features. This representation is conducted for each product. A technique for order preference by similarity to ideal solution (TOPSIS) algorithm [56] is used to rank the different products based on the averaged TFNs computed from the different fuzzy decision matrices.

A fuzzy c-means algorithm was also used for grouping features used by a meta-heuristic optimization technique, called the dragonfly algorithm [28,57], to discover ideal item features from various websites and recommend the best websites based on the ideal features rather than basing recommendations solely on opinions [58].

A fuzzy-rough-based algorithm [59] to extract different features from drug reviews was used in [60]. The algorithm extracts the main words from a Twitter collection using the TF–IDF formula,; then, the terms are associated with sentiments from SentiWordNet and associated with a fuzzy set from 5 predefined sets: [Positive+, Positive, Neutral, Negative, Negative−] whose membership degrees are based on a Gaussian distribution. Tweets are represented as vectors including this fuzzy information from all words forming each tweet. The whole collection is an array that is treated as a multilevel matrix, which is summarized throughout a simplification/reduction process. The result is a set of vectors representing different multilayers of features from the collections and each one associated with the 5 previous sentiment categories. This process yields a set of fuzzy rules whose importance weights are measured via the chi-square tests to calculate the resemblance between features.

Finally, it is worth noting that it is important not only to detect the features but also to know how important they are. A Choquet integral-based feature analysis is performed in [61]. Given the sentiments from the different features in an opinion and the overall rating, the importance of each feature for the different groups of users (couples, families, business, single...) conveying opinions. The Choquet integral allows the analysis of the Shapley values and interaction indices for all features to understand their associated importance as well as the relationship between the different features.

4. Classification

This section is focused on one of the primary tasks in opinion mining. In this case, classification refers to both detecting subjective opinions and recognizing positive, negative or neutral excepts from reviews. This latter task can also involve grading to what extent a review is positive or negative, that is, rating its polarity.

Subjectivity detection. Therefore, before classifying an opinion as positive, negative or neutral, it is necessary to check whether the sentences express subjective information or objective, factual or neutral content, that is, objective information [37]. For example, Chaturvedi et al. proposed an extension on extreme machine learning (EML) for subjectivity detection [62]. First, Bayesian networks are used to build a network of connections among the hidden neurons of a traditional EML approach, with the aim of detecting dependencies in high-dimensional data. Second, a fuzzy recurrent neural network based on the structure generated by the Bayesian networks is implemented as a classifier for detecting subjective sentences. The algorithm was tested against the MPQA corpus composed of Spanish sentences and the multimodal opinion utterances dataset consisting of 498 manually annotated video fragments.

Starting from a previous paper [63], a study of three classifiers (i) the hidden Markov model (HMM), (ii) the adaptive neuro-fuzzy inference system (ANFIS), and (iii) the fuzzy control system applied to subjectivity classification at sentence-level is presented in [64]. Statistical features extracted from text are used to extrapolate the results to any language. A hybrid approach is proposed to combine the results of all the classifies in cases where are not able to correctly detect the class of a sentence.

A simpler approach is found in [65]. It presents a rule-based approach for subjectivity classification whose input is the subjective importance degrees of words (nouns, verbs, adjectives and adverbs) classified into different groups: Highly Subjective, Subjective, Poorly Subjective and Objective. These sets are obtained from a fuzzy c-means algorithm that groups synsets from SentiWordNet, taking into account the polarity values of each term. Each group has associated a weight manually assigned. All the words in a sentence are aggregated according to the polarity values, and if the addition exceeds a threshold, then the sentence is considered subjective.

Therefore, after the information has been determined as subjective, it is possible to classify whether the provided information is positive or negative and to find its associated polarity rating. Then, two main different classification approaches can be found: lexicon-based or machine learning-based.

4.1. Lexicon-based approaches

This type of technique is also called semantic approaches because it is developed on the basis of semantic resources such as thesauruses, ontologies or dictionaries. These tools might be generic or context aware, that is, especially implemented for the domain in which they are applied. Two possible classifications can be distinguished: corpus- or dictionary-based approaches. The latter is context-independent, whereas the former is context-aware. The latter is mainly based on a predefined semantic resource usually containing a structured list of terms/concepts and their associated orientation. Some examples could be SentiWordNet [52], SenticNet [66], SentiWords [67], among others. On the other hand, corpus-based approaches develop a structured or semistructured set of terms from an initial dataset by usually an automatic process that detects not only the terms but also the sentimental orientation depending on the context.

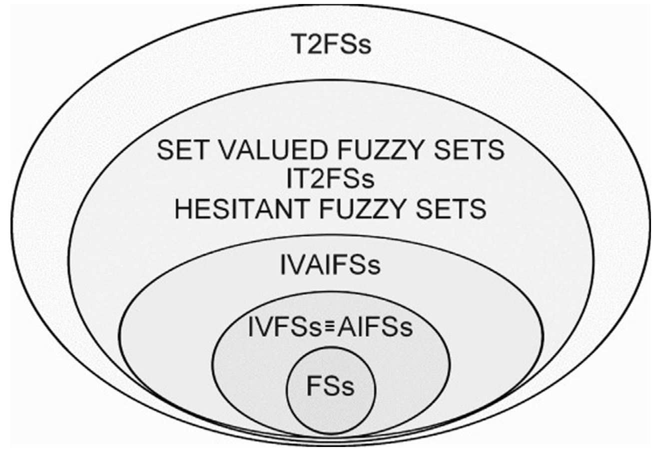

Fig. 3. Fuzzy sets and their relationships [47].

The key core of these techniques is the use of linguistic rules or heuristic strategies by using the knowledge embedded by semantic resources to classify opinions. These semantic resources have also been broadly tested, working in collaboration with machine learning techniques, to develop hybrid approaches obtaining successful results.

Ontologies. With regard to fuzzy ontologies, various projects have implemented specific approaches for sentiment analysis applications. For instance, Ali et al. used a type-2 fuzzy ontology in 2 phases of an algorithm for searching opinions about hotels [68]. The first step is for opinion searching. A user query is preprocessed and expanded to obtain the most adequate opinions from the Web for a specific user. Then, the reviews are split into aspects, and the score orientation of these aspects is computed. This ontology is structured into several features/aspects, associating the typical adjectives for them. The sentiment score of each word is obtained from SentiWordNet, and the orientation of each aspect is the simple aggregation of the different scores of the words belonging to each sentence. The feature polarity is computed through labels based on several rules, such as the following: if (feature polarity $\geq$ 0 and feature polarity $\leq$ 0.25) then opinion = “strong negative”. Thanks to this fuzzy domain ontology previously developed and the information crawled from the Web starting from an initial user query (consumer reviews, hotel information, user data and provider information), a new type-2 fuzzy ontology is automatically developed by gathering all this information.

The fuzzy domain ontology describes the concepts of a hotel feature and its relationship with type-2 fuzzy ontology concepts. Both ontologies are merged, and the opinion polarity is computed through a set of rules defined in the merged ontology, which fuzzifies the opinion words, infers the polarity by executing the corresponding rules and defuzzifies the output to obtain the overall polarity. Ali et al. [69] presented a similar approach, but in this case, they worked only with T1FSs and used only one specialized in the domain of transportation in cities.

A fuzzy ontology-based approach is applied to rating prediction in [70]. A hotel domain fuzzy ontology is defined by including the most important hotel aspects and the opinion words associated, in this case adjectives and adverbs, which are modeled by a fuzzy OWL plugin as fuzzy data types, fuzzy concepts, and fuzzy modifiers. Once these data are modeled, a set of rules considering the different aspects are defined to apply the Delorean reasoner [71] to automatically compute the polarity of a hotel. By a support vector machine (SVM) algorithm, the sentences containing adverbs and adjectives related to the different aspects are detected. The polarity of those words obtained from SentiWordNet [52] is extracted and used to fuzzify the variables to activate the reasoner. Then, the rules are executed, and the polarity is computed and defuzzied in the last step as a crisp value.

In [72], a classical ontology is transformed into a fuzzy ontology via the semiautomatic Protégé plugin called fuzzy OWL as seen in [68] but in this case, simplifying the steps and not including the type-2 ontology, just working the type-1 ontology. The main novelty in this case is the use of an SVM filter for removing irrelevant opinions. An extension of this study is conducted in [73], including some new features, such as a Semantic Web Rule Language (SWRL) rule-based decision-making knowledge, to find the major causes of traffic congestion and negative polarity. An opinion map of the city features and city transportation activities is automatically designed by using semantic knowledge and sentiment analysis results for determining traffic problems and providing safe routes for travelers.

In [74], the fuzzy ontology used in the previous studies has been reused as part of the topic/feature detection process based on latent Dirichlet allocation (LDA), but in this case, the fuzzy values are not used. They are taken into consideration when the opinions are represented by means of a document representation model that uses LDA, word embedding models and the fuzzy ontology to classify opinions. These document representations are used later for other machine learning algorithms for sentiment classification.

An automatic algorithm for generating a fuzzy context-aware lightweight ontology is described in [75]. LDA is used to detect the main aspects, both explicit and implicit, from a product dataset [76]. The main topics are used to detect and model both taxonomic and nontaxonomic relationships between aspects by a probabilistic language model and assigning a fuzzy association degree between nodes in the ontology. Sentiments (adjectives and adverbs) are associated with aspects by a semisupervised statistical context-sensitive learning method. The associated polarity is statistically computed according to the number of positive or negative comments available. These values are interpreted as fuzzy membership degrees that are included in the ontology. The recommendation process based on opinions and fuzzy ontology consists of looking for pairs $\langle aspect, sentiment \rangle$ and calculating the average of all sentiments found.

In [77,78], a methodology for representing fuzzy ontologies applied to domains containing sentiments is explained. The ontology defines a set of opinion words (positive, negative and neutral) for the treated domain and depending on the number of matches against an opinion, it is possible to compute its membership degree regarding a set of three fuzzy sets (low, medium, high) that corresponds to the positiveness degree by applying the formula already defined in [79]. These 3 fuzzy sets are not appropriate for some applications. Therefore, a transformation of the values into a linguistic 2-tuple representation is proposed, which provides a higher granularity scenario. Thus, for example, a concept such as "price" may be represented by qualified fuzzy sets (very bad, bad, normal, good, very good) and the concept "service" by only 3 (bad, normal, good).

A fuzzy ontology is automatically developed by extracting the high-frequency term as features and modeled as a hierarchy [80]. Words appearing in a sliding window close to the features are selected as opinion words (adjectives), and their associated polarity is context-sensitive, so it is necessary to use a training corpus to estimate the polarity as the difference between the number of positive and negative sentiments around a specific aspect. This data item is understood as a fuzzy value. A list of adverbs is manually modeled, and weights are assigned to affect the intensity of sentiments. The sentiment score is determined per review, and the feature sentiment is the mean of all polarities of all words associated with that feature. The polarities must be taken from the ontology or from a sentiment dictionary containing negative and positive words, which is used if the ontology does not contain the opinion word searched.

It is possible to derive conceptual structures from data sets by applying theories such as Formal Concept Analysis (FCA) [81]. Following this idea, Fuzzy Formal Concept Analysis (FFCA) can be proposed as a mechanism for polarity classification (negative, positive) [82]. The main features from text are extracted by three typical measures in information retrieval: TF–IDF, inverted conformity frequency (ICF) and uniformity. These features have an associated fuzzy degree of significance regarding each document in the lattice object set, those under an $\alpha - cut$ are not excluded. According to these degrees, it is possible to establish relationships between concepts and terms and consequently, a lattice. This lattice is used under a supervised learning mechanism which composes fuzzy relationships between term-category and term-concepts to infer the category (positive or negative) to which a document belongs.

[83] proposes a model combining FFCA and concept-level sentiment analysis (FFCA + SA) to manage complaints, that is, negative expressions on customer relationship management (CRM) systems. First, the aspect-level score is computed and then the concept-level sentiment score. Both are computed by FFCA, which is based on a fuzzy context, associating objects with attributes in a fuzzy way. This membership degree is calculated on the basis of the normalized TF–IDF values computed from a document-aspect matrix. Thus, the relationship between an aspect and document is calculated. Then, the aspect-level sentiment score is computed as the aggregation of the different sentiment words found in a sentence that have an entry in SenticNet [66]. These values are normalized to the power of the fuzzy membership degree between a document and an aspect. From these values, the concept-level sentiment scores are computed once some concepts have been previously filtered by aggregating the sentiment scores of aspects related to a concept in all documents of the collection tested.

Dictionaries and thesauruses. From a Twitter collection, a feature space is generated to classify sentiments (positive, negative) in tweets [84]. First, a preprocessing phase detects the main unigram features from the tweets, which are modeled by a BOWs representation. From this representation, a matrix is automatically computed, which connects words according to their correlation degree; this matrix is called a fuzzy thesaurus. The function of this thesaurus is to match the similarity between attributes in the feature space and all terms from any tweet. The matching process is measured by a fuzzy function based on the distance correlation between words [85]. The result is a set of semantic feature vectors that are applied to any classifier (SVM, naïve Bayes, etc.) to predict sentiments.

[3] proposes the development of a context-aware polarity dictionary based on global vectors to compute the neighbors of a term and disseminate guiding polarity values to the rest of the terms. The polarities computed are crisp values that are mapped on different hierarchies of fuzzy labels, following a 2-tuple fuzzy linguistic approach, which might be useful for sentiment analysis-related tasks.

A fuzzy sentiment classifier for Chinese words is designed in [86]. In this case, one of the keys of this algorithm is the manual development of an unambiguous sentiment words lexicon and a sentiment morpheme set from three Chinese sentiment dictionaries. This latter set is made of 2 subsets, one of positive morphemes and another of negative morphemes. The intensity of a word is computed as a function of the frequency of the positive

Table 2
Summary of fuzzy techniques to manage lexicons.

	Fuzzy approach	Article
Ontologies	Type-2	[68] *
	Type-1	[69,70]* [72]
	Fuzzy discrete values	[75,80]
	FFCA	[82,83]
	Linguistic 2-tuple representation	[77,78]
Thesauruses	Type-1	[86,87]
	Fuzzy discrete values	[84] * [88]
	Linguistic 2-tuple representation	[3]

and negative morphemes contained. The fuzzy classifier separates between positive and negative words by using two trapezoidal membership functions whose shape depends on the previously computed intensity of each word. One function is to compute the membership degree for the positive group and the other for the negative group. By the final principle of maximum membership degree, the final class is determined, that is, the word belongs to the class with the highest value from the trapezoidal membership functions.

Zhang et al. proposed a set of POS phrase patterns to determine all possible opinion expressions [87]. These can be categorized into different groups depending on whether they are including for example, negators or adverbs. Different formulas expressed by rules depending on the opinion words compounding each phrase pattern are defined to compute different aggregations. The opinion words are adverbs, adjectives and verbs collected from different collections and grouped into different groups, and each group has associated a triangular-shaped fuzzy set. The review score is computed as the average of the opinion words appearing per feature. The detection of the sentiment words associated with each feature is carried out by a feature opinion mining process that detects different syntactic relationships between opinion words and features. In [88], aspects are classified from text by a naïve Bayes approach. The strength of the associated sentiments is determined by the aggregation of the sentiments from the opinion words found in SentiWordNet, which are also influenced by linguistic hedges such as negators or adverbs, according to Dalal's fuzzy formulas [89].

Most of these resources are based on statistical techniques; hence, it is possible to apply them to different languages, just tuning some parameters [90]. Table 2 summarizes the fuzzy techniques used for managing the lexicons for each study. The asterisk * indicates that those references are based on the use of SentiWordNet apart from a specific ontology or thesaurus.

4.2. Machine learning-based approaches

There are several families of strategies to follow when dealing with classification: supervised strategies, semisupervised and unsupervised, but most of the papers found are supervised, following different approaches as are depicted in Fig. 2.

Next, the studies analyzed here are classified into four supervised categories (rule-based, graph-based, probabilistic and deep learning-based), including another subsection for unsupervised approaches.

4.2.1. Rule-based approaches

A fuzzy 9-rule-based system is implemented in [91], in which the words from different tweets are preprocessed and the sentiment-bearing words are extracted. The sentiment orientation of a word is measured into 2 categories, how positive and how negative (low, neutral or high) is, and the associated sentiment score is computed as the aggregation of the positive and negative scores of said words from 3 lexicons: SentiWordNet [52], AFFIN [92] and VADER [93]. The score of these two variables is used as a membership function to activate the 9 rules of the system, which computes the overall rating for the whole opinion (neutral, positive or negative).

A rule-based system is proposed [94] on the basis of several emotions from a lexicon [95]. These emotions are treated as fuzzy variables modeled by fuzzy sets (Low, Medium, High), which are antecedents of several rules, generating the sentiments (Very Negative, Negative, Neutral, Positive, Very Positive) associated with the opinions as an output. The importance of each rule is manually assigned. The strategy is tested with tweets, which are preprocessed, and the sentiment words are aggregated depending on their different emotions, activating the rules to compute the overall opinion rating.

In [51], the primary words from a Twitter collection are extracted according to the TF–IDF formula. These terms are associated with sentiments from SentiWordNet and a set of five fuzzy sets [Positive+, Positive, Neutral, Negative, Negative−], whose membership degrees are based on a Gaussian distribution. The tweets are represented as vectors that include the fuzzy information from all the words forming each tweet. The entire collection forms an array treated as a multilevel matrix, which is then summarized using a simplification/reduction process. The result is a set of vectors that represent different multilayers of features, and each one is associated with one of the 5 sentiment categories [Positive+, Positive, Neutral, Negative, Negative−]. This process yields a set of fuzzy rules whose importance weights are measured via chi-square tests to calculate the resemblance between features.

A rule-based approach was proposed in [96] to classify opinions as positive or negative within the range $[-3, +3]$. An algorithm based on term frequency extracts the most relevant terms. These terms represent the language rules that will be used to classify opinions. To estimate all the classifier parameters, a particle swarm optimization (PSO) algorithm is used to estimate the membership functions, the required fuzzy rules, and the required number of rules, all without user intervention. After the rules have been detected, it is possible to execute the algorithm according to the data from the test collections.

Dalal et al. proposed a lexicon-based approach for fine-grained feature-based classification ("very positive," "positive," "neutral," "negative," and "very negative") [89]. The feature detection is based on detecting different POS patterns. The main novelty in this approach is its use of fuzzy formulas to model the effects of detected modifiers, concentrators, and dilators along with opinion words. The algorithm obtains the polarity degree of the opinion words from SentiWordNet and uses this value as the initial membership degree of any feature descriptor. Finally, using the fuzzy values describing the features, a very simple fuzzy-rule-based system is designed to classify the reviews.

On the basis of Wang–Mendel method [97], several fuzzy variables are modeled, and fuzzy rules are automatically generated across 60 textual document features. These rules are used by a fuzzy inference system to classify opinions [98]. The opinions are preprocessed by extracting different features; for instance, all the POS tags are extracted (primarily to detect adjectives and adverbs) and their associated polarity is assigned through SentiWordNet. Among all these textual features, the most relevant are filtered by correlation-based feature selection [99] and the C4.5 algorithm [100]. The resulting features are modeled as linguistic variables, divided into three fuzzy sets (low, medium and high) and input to a fuzzy rule-based classifier. After modeling the fuzzy sets, the Wang–Mendel method is applied to generate fuzzy rules. Then, these rules are used to generate the classification for a fuzzy inference algorithm based on the general fuzzy reasoning method and the classic fuzzy reasoning method [101].

Following the same previous idea, in [102], documents from movie reviews are preprocessed to extract the n-grams that are useful for classifying sentiment [98] for those particular textual features. Then, different fuzzy rules are generated from those features by [97]. The resulting rules are simplified by the non-dominated sorting genetic algorithm NSGA-II [103] to improve the execution time while still obtaining similar results.

Cosma et al. preprocessed reviews to extract the primary terms and represented them by a vector space model [104]. This information was then simplified by singular value decomposition and dimensionality reduction techniques. Then, a fuzzy c-means algorithm was applied to group the reviews. By applying [105], a Takagi-Sugeno-Kang rule is assigned to each resulting cluster to determine the membership degree of each review to a particular cluster. These rules form the input to an ANFIS algorithm that predicts the rating of each review.

An evaluation of the collective perception of, for example, an urban area or a monument, can be conducted based on comments from blogs. These comments are preprocessed by extracting the main keywords, which are then manually revised. Using SentiWordNet, it is possible to compute how positive, negative or neutral a word is based on the average of all the provided values. These values are proposed to form the membership degrees for the input variables of a fuzzy if-then rule system whose inputs are the variables (positive, negative and neutral) and whose output is the collective perception of the urban area or monument [106]. This previous study was extended by including fuzzy collective perceptions as part of a fuzzy cognitive map (FCM) [107], which made it possible to establish relationships among all the points of interest of a city [108].

A fuzzy rule-based system for tweet classification was detailed in [109]. A nine-rule system was designed that uses two parameters called positivity and negativity as inputs. The system outputs the membership degree of a tweet with regard to a class (positive, negative or neutral). The positivity and negativity values are computed by common semantic similarity metrics from the information retrieval field to measure the similarity between a tweet and two ideal documents, one negative and another positive, containing words describing positivity and negativity, respectively. These metrics are fuzzified by trapezoid-shaped membership functions to form inputs for the system.

In [110], another fuzzy rule-based system was proposed that takes adjectives, adverbs and verbs as inputs. Triangular membership functions were applied to all the opinion words, and a set of fuzzy rules was manually designed to ensure that all possible combinations of opinion words were covered. To select the best combination of rules, they used the shuffled frog leaping algorithm, which is a metaheuristic approach combining properties from mimetic algorithms and PSO [111]. Different feature vectors were extracted from Amazon book reviews to optimize the system rules and obtain the best possible sentiment classification.

Feature selection is essential in sentiment classification [112]. In this case, the key features are morphemes. A C4.5 decision tree and a map-reduce algorithm were used as a frequent pattern mining algorithm to find patterns among the morphemes. Subsequently, a biobjective algorithm optimization approach was used to select the most suitable features and finally classify tweets into five categories (positive, negative, strongly positive, strongly negative and neutral) by a (logistic regression)-based ANFIS algorithm. In this case, logistic regression was used to avoid the need to increment the fuzzy rules when many features are processed by the ANFIS algorithm.

In [48], Afzaal et al. utilized fuzzy logic in 2 algorithm steps to extract aspects (as explained in Section 3) and classify opinions. To classify the detected aspects, a fuzzy rule-based algorithm called FURIA [49] was used. To classify the opinions as positive or negative, different algorithms were implemented that used the aspects previously detected. The authors evaluated which classification algorithm obtained the best results. The tested algorithms were FURIA [49], fuzzy KNN and a variant that studies with fuzzy rough sets called the fuzzy rough nearest neighbor [113], vaguely quantified nearest neighbors, which is a variant of the previous algorithm, and finally, fuzzy lattice reasoning (FLR) [114]. All the algorithms were tested using a set of opinions from TripAdvisor. FLR and FURIA outperformed the other algorithms. In addition, Jefferson et al. proposed a Tsukamoto rule-based system [115] and tested it against 5 binary movie datasets (classified as positive or negative), but this study did not clearly explain the fuzzy membership functions used for testing. One of the datasets was divided into some additional categories (somewhat negative, neutral, somewhat positive and positive).

Apart from detecting whether a tweet is positive or negative, other types of classifications can be conducted. For instance, a rule-based system for hate speech was studied in [116]. To define whether a tweet involves hate speech, they authors defined seven features and modeled them by fuzzy sets that are used to define fuzzy rules to classify the tweets. When any doubt exists regarding whether a tweet contains hate feelings (ambiguous instances), the study applied a mixed fuzzy rule formation algorithm. This algorithm adds new rules or modifies the initial rules to retrain the system depending on the ambiguous instances [117]. Therefore, it is a two-step algorithm; when the classification is clear in the first step, the second step is unnecessary; otherwise, the second step is executed.

Table 3 summarizes the studies about this section:

4.2.2. Graph-based approaches

A multidomain sentiment analysis proposal was implemented in [119,120], which used a two-layer network consisting of an initial semantic layer that models the different concepts and relationships among them as well as the different domains of the dataset, and a second layer that models the sentiments of each concept. The fuzzy membership degree of each concept in a specific domain was computed by analyzing the explicit information from the dataset, and a preliminary fuzzy membership function was estimated based on the semantic level of the graph and the domains found at the sentiment level. The second step is an iterative propagation process that calculates the fuzzy membership degree of each sentiment based on the influences of similar concepts. The concepts are linked and propagated through an integration of WordNet and SenticNet. Finally, the polarity of each complete document is determined by aggregating the membership degrees of all the found concepts using Zadeh's extension principle. In [121], an extension of the previous studies was presented that included new and refined formulas for computing the initial polarities of the concepts and for aggregating the fuzzy values to compute the overall document rating. Instead of using WordNet as a means to connect terms in the semantic layer, this study used the General Inquirer[1] is used.

Joshi et al. computed tweets polarity according to different fuzzy labels (good, better, best, bad, worse, or worst) [122]. First, this method computed sentiments from hashtags at the entity level using a well-known graph-based hashtag sentiment classification algorithm [123]. Then, the tweets are preprocessed by extracting the main words that bear sentiments. A lexicon-based approach extracts the polarity based on SentiWordNet or an emoticons dataset, consisting of 45 emoticons with corresponding polarities. All the words are combined to yield a final normalized polarity score (good, better, best, bad, worse, or worst).

[1] http://www.wjh.harvard.edu/~inquirer/spreadsheet_guide.htm.

Table 3
Summary of rule-based techniques.

	Resource	Article
Rule-based approaches	SentiWordNet	[96,98,102,106,108]
	Crowdsourcing lexicon [95]	[94]
	SentiWordNet, AFFIN and VADER	[91]
	–	[110,115,116,118]

A hybrid method combining graphs and fuzzy SVM (FSVM) is presented in [124]. FSVM is based on the idea that each sample contributes differently to the classification process. In this case, the fuzzy membership degree of each sample is calculated by a 3-layer propagation model, in which the layers represent documents, topics (extracted by LDA) and words. The model representation is a directed graph that can be split into nine matrices. An iterative process was used to compute the neighbors in the network based on intensity measured via the TF–IDF values of the terms and LDA's parameters. The final result is a sentiment membership degree for any document resulting from a composite of the neighbors' intensities. These documents are used to train an FSVM to classify and detect the ratings for new documents.

Most graph-based approaches require the use of both semantic and sentiment resources, that is, they implement hybrid solutions. A summary is listed in Table 4:

4.2.3. Probabilistic-based approaches

In [125], all the words in phrases from tweets regarding *energy* in Alaska were extracted using a lexicon from TextBlob.[2] The aggregation of the sentiment scores from all the words in each phrase were used to map 4 fuzzy labels in the range $[-1, 1]$ representing a two-dimensional valence–arousal space. These 4 labels (high positive, low positive, low negative, and high negative) are represented by Gaussian functions. After each phrase has been associated with a label, the aggregation of the different phrases' sentiment scores is based on the Dempster–Shafer theory and used to finally compute the tweet sentiment score.

4.2.4. Deep learning-based approaches

Apart from the typical machine learning techniques, note that newer artificial intelligence techniques are rapidly gaining influence, such as deep learning techniques. Some studies exist that are related to sentiment classification and combine fuzzy logic and deep learning. For instance, Vashishtha et al. proposed a long short-term memory (LSTM) classifier whose input is a set of cognitive words that best describe the sentiment in any opinion [126]. This set of cognitive words is detected by a fuzzy entropy measure that grades sentiment words by differentiating between insignificant (high entropy) and significant (low entropy) words. This measure is computed via the sentiment values obtained from SentiWordNet. Following this study, the same authors proposed a mechanism for document-level sentiment classification based on highlighting keyphrases [127]. The keyphrases are detected by a fuzzy entropy filter and k-means clustering, and their associated polarities are computed by means of fuzzy linguistic hedges and SentiWordNet [52].

In [128], 4-dimensional common sense vector called AffectiveSpace is used to predict positive, neutral and negative sentiments in multimodal content. First, a convolutional fuzzy sentiment classifier is used to obtain features and project them onto the AffectiveSpace. The input to this classifier is the ranges of the values in four dimensions (pleasantness, sensitivity, attention and aptitude), each of which is delimited in a range between max and min values [min, max]. These intervals can be split into additional subsets to achieve a finer-grained classification (e.g., joy, anger, surprise), modeled by membership functions and labeled "high", ..., "low", representing the extent to which a concept belongs to an emotion. The features detected by a convolutional deep belief network are projected onto these emotions and input to a recurrent neural network, which uses a fuzzy classifier that gives the result as a class (positive, negative or neutral) of the data assessed.

Wang et al. proposed an information-geometry-enhanced fuzzy deep belief network for polarity classification [129]. Most fuzzy clustering algorithms working with neural networks consider the features that represent the reviews but not the feature distributions; however, in this case, the distance between features measured by the information geometry is considered. Then, the features are used to detect different fuzzy patterns using a fuzzy clustering algorithm whose fuzzy clusters are the input to the deep belief network, which is trained to classify the sentiments in the reviews.

4.2.5. Unsupervised approaches

Beyond simply detecting whether a sentence or tweet is positive or negative, other approaches can detect whether it is was intended to be sarcastic or not. Mukherjee et al. compared two algorithms to automatically detect sarcasm in tweets labeled either #sarcasm and #notsarcasm [130]. The tweets were preprocessed by extracting content words (meaningful words), function words (nonmeaningful words), POS, n-grams, content words + function words, function words + N-grams, and content words + function words + POS n-grams. The extracted words are used as features for two classifiers based on fuzzy c-means and naïve Bayes. In this case, naïve Bayes clearly outperforms the fuzzy c-means algorithm. Another three-cluster solution (positive, negative and no-opinion) for tweet classification based on fuzzy c-means can be found in [131].

5. Emotions

Affective computing is a research field "concerned with giving computers the ability to recognize, express, and, in some cases, 'have' emotions and other related affective phenomena" [132]. The terms sentiment and emotion are used interchangeably by most people; nevertheless, there are some differences. A sentiment is "an attitude, thought, or judgment prompted by feeling, a specific view or notion", whereas an emotion involves "excitement, the affective aspect of consciousness; a state of feeling; a conscious mental reaction (as anger or fear) as strong feeling usually directed toward a specific object" [133]. Furthermore, according to Cambria, sentiment analysis can be considered a branch of affective computing. Both fields are extremely connected, and polarity detection is closely related to emotion detection [134].

Fuzzy logic has also been broadly used for tasks related to emotion detection and characterization. For instance, in [135], an emotion vector is used to represent each sentence from a tweet. Each value in the vector represents a fuzzy membership value for Ekman's emotion classes (happiness, sadness, anger, fear, surprise, and disgust) [136]. These values are generated by analyzing semantic resources, such as a collection of hashtags, emoticons or interjections. To aggregate all the values to compute the tweet emotion rating, the authors proposed a semantic

[2] https://textblob.readthedocs.io/en/dev/quickstart.html.

Table 4
Summary of graph-based techniques.

	Techniques	Article	Resources
Graph-based approaches	2-layer net: semantic and sentimental	[119,120]	WordNet and SenticNet
	2-layer net: semantic and sentimental	[121]	General Inquirer
	Graph-based hash tag sentiment classification algorithm	[122]	SentiWordNet and emoticons dataset
	3-layer propagation model and FSVM	[124]	–

measure based on a multilayer perceptron neural network that measures the relatedness degree between sentences containing the same emotion.

Working with the hourglass of emotions model [137], which proposes 4 dimensions, each of which is divided into 6 sentic levels (emotions), Brenga et al. preprocessed opinions to obtain relevant words and associated them with a WordNet synset [138]. This synset is associated with WordNet-Affect's dimensions based on the semantic distance between the synset and the dimensions. Different sentic levels can be found for a word, but to acquire a unique view of the word, it is necessary to aggregate all these levels. Therefore, the dimensions are modeled by linguistic variables, while the emotions are modeled by 7 fuzzy terms (limbo is also included) and aggregated by the linguistic ordered weighted averaging operator (LOWA) operator [139]. The intensity of a word is also affected by adverbs, which are calculated by other formulas. This aggregation process can be applied at either the sentence or document level. To improve this approach, two ontologies were proposed to map the sentic level in the hourglass model and the relationships between Wordnet and SentiWordNet, called EmotiSLOS and SentiWordSKOS, respectively [140].

A two-step algorithm was implemented in [141] to automatically compute an emotion lexicon. First, an unsupervised fuzzy c-means algorithm was executed, which took as input features such as emotional statements of the international survey of emotion antecedents and reactions (ISEAR) dataset [142], WordNet's distances, and the similarity of the polarity scores in SenticNet. Second, the fuzzy clusters obtained were input, along with the other features, to a supervised algorithm such as an SVM.

A fast extension of the well-known fuzzy c-means algorithm was presented in [143] to classify tweets in accordance with their emotions. First, the words were manually classified into 8 emotional categories: open, happy, alive, good, love, interest, positive, and strong. Only words belonging to those categories were used to represent each sentence from a tweet. The TF–IDF measure of all these words is then used as a feature into the extended fuzzy c-means algorithm. Each resulting cluster is labeled by the most predominant emotional category.

An affective clustering model based on a Gaussian-based affective Valence–Arousal–Dominance (VAD) space model [144] and an extended fuzzy c-means algorithm was described in [145]. A Mandani rule-based inference system is developed from the clustering results to assess the performance of the clustering algorithm grouping of adjectives from different questionnaires about chairs.

In [146], a fuzzy convolutional neural network was developed solely to analyze sentiment in text. In [147], a more complex version was presented that addressed multimodal emotion understanding. The fully connected layer of the former study was replaced by an ANFIS classifier, which fuzzifies the first layer features from text, audio, and video content to transform them into a high-level emotion feature representation. The last layer defuzzifies the output to classify the emotions found.

SenticNet 1.0 lacked emotion labels, and a semisupervised algorithm was proposed to enrich this resource [148]. In this approach, different features taken from the ISEAR dataset [142] and similarity measures established between concepts in resources such as SenticNet, Wordnet and ISEAR are used to assign emotion labels to SenticNet's concepts. The features are first categorized by a fuzzy c-means algorithm that recognizes six categories that will be identified as different emotions from Wordnet-Affect. Because the fuzzy c-mean algorithm results were not sufficiently accurate, an SVM algorithm was used as a disambiguation mechanism when the label assigned to a concept was unclear. A case study can be found in [141].

In [149], a new framework called EmoSenticSpace was developed that combined other resources such as WordNet-Affect and SenticNet to provide emotion labels and polarity scores. By reusing most of the features from [148], another semisupervised algorithm was implemented by combining fuzzy c-means clustering and SVM to develop a new resource for affective commonsense reasoning. In addition, based on the ANEW dictionary and WordNet, a label propagation algorithm was developed to expand the properties of words from WordNet, including valence, arousal, and dominance values, creating an affective lexicon [150]. When a word does not appear in Wordnet, default values are used. Features based on these values, such as words with negative valence, arousal, and dominance, were used to train a FSVM to achieve sentence-level sentiment classification.

Loia et al. presented a fuzzy characterization algorithm for sentiment and emotions. The polarity, P, is described as a fuzzy set represented in a triangular form, i.e., $(-1, 1, 1)$ [79]. Thus, each word w has a membership degree in the range [0, 1] based on the function $P(w)$. Likewise, an emotion E is described by a triangular fuzzy set whose membership function is represented by $(0, 1, 1)$. Hence, given a word w, the associated emotion can be computed by mapping $E(w)$ onto the space [0, 1]. In this case, adjectives are considered as providing emotions and feelings, and they can be affected by adverbs, negators and other meaning-shifters in what Cambria terms a *sentic pattern* [151]. Their effects can then be calculated as follows:

$$\mu_{adv(P)}(adj) = \sqrt{(P(adj))} \text{ if } P(adj) \geq 0.5$$

$$\mu_{adv(P)}(adj) = P(adj)^2 \text{ if } P(adj) \leq 0.5$$

As an example of a negation is as follows:

$$\mu_{neg(P)}(adj) = 1 - P(adj),$$

while an example of combining negation and adverbs is

$$\mu_{neg+adv(P)}(adj) = \sqrt{P(adj) * \mu_{adv(P)}(adj)}.$$

Finally, the polarity or emotion of a sentence is computed as the mean of all the polarities of all the sentiment or emotional words from the sentence. For an entire tweet, the polarity or emotion is the mean of all the sentence polarities/emotions.

Following the idea of sentic patterns, Serrano et al. [152] presented an emotion-driven polarity detection mechanism based on the SenticNet [66] and the use of the T1OWA operator. This mechanism allows explaining the opinion scores based on the user mood. Depending on his/her mood or character, the user decisions can be more influenced by positive or negative opinions. An optimization process tunes the weights W of the T1OWA operator to model different types of users: optimistic, balanced or pessimistic.

In [153], historical tweets from the Manchester United Football Club were collected and preprocessed, and terms that appear in the LIWC dictionary [154] regarding anger, sadness, and 'positive' emotions were extracted. This dataset contains 65 different linguistic variables along with the numbers of tweets and retweets posted per hour. For the linguistic variables related to emotions, the universe of discourse is split into different subintervals int_i, which are used to represent several fuzzy sets A_i. For instance, a fuzzy set A_1 can be represented as $A_1 = 1/int_1 + 0.5/int_2 + 0/int_3 + \cdots + 0/int_{18}$ and used as input for three different fuzzy approaches that were studied. The first is a fuzzy temporal series based on Chen's ideas; the second uses the fuzzy temporal series as an input to train a feed-forward artificial neural network (ANN) model; and finally, the third uses an ANFIS model that combines the self-learning ability of an ANN with the advantages of logical inference systems. The results of the experiments showed that the last model outperformed the first two.

As described above, the use of semantic resources is vital for most emotion-related tasks; consequently, most of the articles described represent hybrid approaches, combining the use of lexicons and machine learning techniques. In Table 5, the reader can see a summary of the used fuzzy logic-based techniques, as well as other necessary techniques, and the necessary lexicons.

6. Applications

In real-world applications, opinion mining is seen as a trendy field due to the growing number of related applications developed in recent years. Tools, especially Internet-based tools such as search engines, social networks, and eCommerce platforms, have fostered improvements to classical applications and engendered new ones related to opinion mining, such as recommender systems, opinion retrieval systems, stock market forecasting systems, and political analysis systems. Among these applications some that implement fuzzy logic-based mechanisms are described below.

6.1. Opinion mining in the stock market and stock forecasting

A sales prediction system that predicts next weeks' sales based on sentiments regarding the tweets from previous weeks is described in [156]. A lexicon-based naïve Bayes classifier is implemented to detect different classes for tweets (positive, negative or neutral), and a time series model whose input is a corrective coefficient is used to predict sales. This method attempts to measure the probability of a product sale based on people's opinions extracted from tweets in the previous weeks. This coefficient is the output of a fuzzy rule-based system whose inputs are the membership degrees of the variables "positive", "negative" and "neutral" calculated by the naïve Bayes classifier.

In [157], tweets are represented by their primary words, and the associated sentiments are represented by fuzzy sets (positive, objective, negative) using a semantic approach based on SentiWordNet. The associated fuzzy values are discretized by a first of maximum (FOM) algorithm, and the sentiment rating is computed using an aggregation formula that considers all the individual words in a tweet. The resulting information is used for sales predictions.

The authors of [158,159], used Twitter opinions to predict the Dow Jones Industrial Average (DJIA) over time. The opinions were preprocessed by OpinionFinder to obtain time series data regarding sentiments (positive or negative). Furthermore, this study used the Google profile of mood states (GPOMS) tool to classify the moods of the different tweets into 6 categories: calm, alert, sure, vital, kind, and happy. These time series, along with the past 3 days of DJIA values, were input to a self-organizing fuzzy neural network model to predict up and down changes in the DJIA.

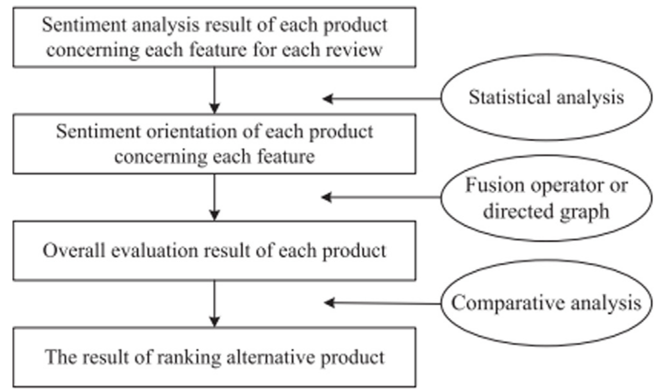

Fig. 4. The process of information fusion based on online review sentiment analysis [34].

The sentiment scores of user product preferences in different periods were computed using time series data in [160]. First, the authors implemented a SentiWordNet-based approach to compute a sentiment score for each product preference. Then, the min, max, and average of all sentiments were computed to represent the overall sentiment for a specific time period as a TFN (min, ave, max). From these values, a dynamic evolving neural-fuzzy inference system (DENFIS) [161] was implemented to predict the sentiment based on user preferences in subsequent time periods.

6.2. Opinion summarization and retrieval

A recommender system was presented in [162,163] that combined sentiment analysis and fuzzy quantification methods for qualitative data. The system generates short summary sentences as follows. First, a parser looks for sentences that include linguistic quantifiers such as "most of" or "about half". Second, a preprocessing step extracts the POS tags of all the terms in a sentence and detects sentences containing nouns related to possible aspects of hotels. Third, a semantic orientation mechanism based on pointwise mutual information (PMI) is used to reduce the number of terms analyzed as aspects of a restaurant or hotel. The adjectives are represented by the score from SentiWordNet, and the quantifiers are modeled by fuzzy sets to compute the average polarity of any sentence. The generated summaries follow the form "most of the guests think/say that the place(s) was/were great". Each summary has an associated truth degree that depends on how much supporting information it is present.

Other applications related to fields such as opinion retrieval can be found. For instance, [164] describes a web query language called FSA-SPARQL (Fuzzy Sets and Aggregators based SPARQL) that allows social network to be consulted based on fuzzified information related to sentiment analysis, such as sentiments associated with tweets.

6.3. Multicriteria decision making applications

Many studies have been performed to rank products based on various criteria. In this case, we present only those papers that do not solely consider aspects/features as criteria; these studies clearly involve opinion mining tasks such as extracting features from product reviews and aggregating those values to rank the products. Fig. 4 depicts a scheme for product ranking based on information fusion that represents most of these studies [34].

Despite the fact that most of the studies focus on working at the document level, Appel et al. are more interested in working at the sentence level. Thus, rather than aggregating features

Table 5
Summary of emotion-based studies.

Article	Lexicons	Fuzzy logic-based techniques
[135]	Collection of hashtags, emoticons and interjections manually classified.	Fuzzy values (aggregated by a Multilayer perceptron neural network)
[138]	WordNet-Affect	LOWA aggregation operator
[140]	EmotiSLOS and SentiWordSKOS	LOWA aggregation operator
[141]	SenticNet, WordNet and ISEAR	Fuzzy c-means (and SVM)
[143]	Manual classification	Fuzzy c-means
[147]	COGNIMUSE database [155]	ANFIS
[148]	WordNet, ISEAR and Wordnet-Affect	Fuzzy c-means (and SVM)
[149]	WordNet-Affect and SenticNet	FSVM and fuzzy c-means
[152]	SenticNet	T1OWA aggregation operator
[153]	LIWC	ANFIS

to compute the overall rating of a document, the authors aggregate the polarity from the individual sentences comprising a document. For instance, a SentiWordNet-based approach was implemented in [165], although human interaction is required to refine the results. The sentence polarity variable is represented by five trapezoidal fuzzy sets (poor, slight, moderate, very, most). After the sentences have been rated, the minimum polarity of all the words extracted from the lexicon is used to compute the membership degree for these 5 fuzzy sets; the maximum is used as the sentence polarity intensity. Other proposals based on uninorms are posed as future challenges. Following that idea, in [166], a hybrid mechanism was proposed based on 5 factors: sentiment lexicon, semantic rules, negation handling, ambiguity management and linguistic variables. An automatically computed lexicon to acquire word orientation that followed Hu and Liu's algorithm [167] was used to compute word polarity. However, sentence orientation was calculated only after preprocessing all words, detecting their POS tags, filtering them based on several POS-based patterns, and handling ambiguity, subsentences and negations in said sentences.

In addition to this approach, individual words can be used as units to be aggregated to compute the final polarity of a document. In [168], 1030 words from Affective Norms for English Words (ANEW) [169] were grouped by a k-means clustering algorithm; then, the dimensions were reduced by principal component analysis (PCA). Finally, a hierarchical clustering algorithm was executed to classify the words into 4 categories (very positive, positive, negative and very negative) represented by fuzzy sets. The ANEW values for each word were normalized to the range [0,1] and used to map each word polarity to a fuzzy set with a trapezoidal-shaped membership function. The aggregation of all the opinion words from a tweet represents its polarity. Nevertheless, it is not necessary to aggregate all words to compute the overall polarity. In [170], the use of the Choquet integral is proposed, in a theoretical way, as a possible mechanism for computing the overall polarity considering only the most important term in sentence or document.

A methodology for assessing products based on sentiment ratings represented by hesitant fuzzy linguistic term sets and an associated measure about the consensus reached by the opinion holders was presented in [171]. All the opinions are preprocessed to find words shared with the AFINN dictionary [92]. Depending on the words compounding an opinion, these provide positive or negative effects on the overall rating. This effect is measured by considering the frequency with which the words appear in the opinion and their valences from AFINN. The associated hesitant fuzzy linguistic term sets are computed from all the opinions based on those effects, and the centroid is calculated as the overall polarity.

The use of multiple classifiers can be interpreted as similar to several experts expressing their opinion about the sentiment of a text. Different fuzzy aggregation operators can be utilized to compute the final score or classification based on the importance of each classifier. For example, Wang et al. implemented a generalized ensemble learning scheme that combined different online sequential extreme learning machines [172]. The output of these classifiers is represented as intuitionistic fuzzy sets (IFSs) that are aggregated by the I-IFOWA operator and used to predict the polarity of the text (positive or negative). The IFSs represent the probability of a test pattern, composed of different features extracted from the reviews belonging to a class (positive or negative) and consequently, the probability that a test pattern does not belong to the same class. The problem can be interpreted as a decision-making problem where classifiers aggregated based on their accuracy provide different opinions, and a weighting scheme is used to obtain the final opinion classification. In addition, [173] described a fusion algorithm that combined the output of different classifiers (SVM, naïve Bayes) using maximum entropy or natural language processing techniques. The outputs of these classifiers are represented as a prediction profile, which form the training data for a heuristic least mean squares algorithm. This algorithm learns the diversity of each classifier as a fuzzy measure. The Choquet integral is used as an operator to aggregate the output of all the classifiers by considering the best combination according to their diversity.

Nevertheless, most MCDM-based studies have focused on aggregating the polarities of the different features characterizing a product. Thus, in [7], the collective sentiment orientation toward a product is represented by type-2 fuzzy numbers (T2FNs). TFNs $G = (g^l, g^m, g^u)$ are used to represent the collective sentiment orientation toward a product, where g^l, g^m, g^u represent the percentage of negative, neutral and positive opinions, respectively, collected about that product. Because some uncertainty μ exists regarding how effective the opinion classification process (negative, positive and neutral) is, the collective opinion can be represented by interval T2FNs in the form $G = [(g^l, g^m, g^u, 1), (g^l, g^m, g^u, 1)]$. Using this representation of the collective sentiments for every feature from each product, a product ranking algorithm was proposed based on an MCDM approach. The ideal and anti-ideal products are computed using a matrix representing all the features/aspects to rank all the products by a closeness measure between each alternative product. In these experiments, the polarity was computed by the algorithm described in [174].

In [175], the sentiments toward product aspects are represented by T1FSs obtained from a predefined scheme and aggregated by the T1OWA operator [176], whose associated weighting vector W is modeled by the user preferences. In this way, an MCDM-based recommender system was designed to provide customized product recommendations based on user preferences.

In [55], a fuzzy c-means algorithm was used as part of the process to determine the aspects of the products to be ranked. First, a preprocessing step was used to detect nouns as explicit features; then, a cooccurrence association rule mining process inferred implicit aspects. These aspects were grouped into different units by the fuzzy c-means algorithm. The opinion words (adjectives) and aspects were associated by an undirected graph, and a graph-based coranking algorithm was used to select the features for each product. The opinion words were classified into five categories (very good, good, medium, poor and very poor) represented by the given TFNs. A fuzzy decision matrix was generated for each feature that included the fuzzy values of the opinion words linked to the different features. This representation process was conducted for each product. Finally, the TOPSIS algorithm was used to rank the different products based on the averaged TFNs computed from the different fuzzy decision matrices.

A doctor ranking system based on multicriteria group decision making (MCGDM) was presented in [177]. Different aspects were extracted from the website Haodf.com and used to rank the doctors. The weights of each aspect/criterion were calculated using the TF–IDF formula, and the adjectives for each aspect were analyzed and manually represented by different interval-valued fuzzy numbers (IVFNs). The number of IFNs per aspect differed depending on the characteristics of the aspects. Again, the final ranking was calculated using TOPSIS.

A HowNet-based algorithm [178] was proposed to classify product feature sentiments in [179]. To represent the sentiments of opinions on features in a fuzzy way, interval-valued intuitionistic fuzzy numbers (IVIFNs) were used to represent positive and negative degrees [pos, neg]. These degrees were computed as the percentages of positive or negative opinions found throughout the total number of reviews. Based on these fuzzy numbers and weights provided by the user, the TOPSIS algorithm was executed to rank various products.

In [180], three SVM classifiers, one for each sentiment (positive, negative or neutral), were trained using manually labeled sentences for each aspect of the evaluated products. The results of these three classifiers were combined using a one-vs-one (OVO) strategy. This study used an identical mechanism to represent sentiments by IVIFNs as was reported in [179], but the values [pos, neg] were refined by considering their confidence degrees because the values can be biased based on the number of crawled reviews.

A lexicon-based approach was presented in [181] in which the lexicon was generated from seed words categorized manually based on the different features detected (primarily based on adjectives) and extended using SentiTurkNet [182]. Sentence by sentence, the opinions are preprocessed and each found sentiment-bearing word is associated with an aspect using the lexicon and the word's polarity. Every sentence related to a specific feature was classified as positive, negative or hesitant depending on whether the number of positive aspects was larger than the number of negative aspects, and vice versa. When both values were equal, the sentence was classified as hesitant. This solution adopted IVFSs to represent the user's degree of satisfaction, dissatisfaction or hesitancy depending on each criterion/aspect. The percentage of positive, negative and hesitant sentences was used to calculate the membership and nonmembership degrees of each aspect. The IVFSs were used to compute how well a product satisfies a feature/criteria. Finally, an MCDM approach was applied to rank the different products.

A decision-support system was implemented in [183] to rank products. In this case, the reviews were modeled by linguistic IFSs because it can be unclear whether the sentiment in an opinion is positive or negative. All linguistic IFSs for each aspect of a product were modeled by a cloud [184], and the result was a linguistic intuitionistic normal cloud (LINC). The aggregation between the aspect weights and the sentiments modeled by this cloud was performed by two novel operators, one based on the weighted average and the other on the Bonferroni mean to include the correlation between aspects.

A different approach appears in [185], in which the opinions are represented by probability multivalued neutrosophic numbers (PMVNNs) for each meaningful unit for each aspect/criterion. The PMVNNs were computed after a sentiment analysis process executed using the R-project's functions. The weights of the different criteria were computed via TFNs following the fuzzy analytic hierarchy process (AHP) method in [186]. Finally, the implemented ranking algorithm follows the qualitative flexible (Qualiflex) multiple criteria method [187].

Peng et al. began by applying a typical preprocessing step to extract the POS tags of each word and its frequency [188]. The resulting words are grouped with their closest synonyms using the Chinese software WordSimilarity based on HowNet. These groups/aspects are modeled by five TFNs, assigned by five domain experts. The averaged TFNs are used to model a fuzzy decision matrix, which forms the input to the fuzzy PROMETHEE algorithm used to rank the different products [189].

A sentiment prediction MCDM model was proposed in [190]. All the opinion word-aspect pairs were detected using a deep learning approach based on a bidirectional LSTM network and conditional random fields. All the words were represented by a word2vec language model and clustered to correctly characterize the aspects of any product. Each word has an associated sentiment (positive, negative and neutral) acquired from a lexicon developed from both an eCommerce sentiment dictionary and a Chinese sentiment ontology library. The associated sentiments (negative, neutral and positive) and their aspects are computed as the mean of all the sentiments associated with the words for each sentence that refers to that aspect. The positive and negative values are represented by q-rung orthopair fuzzy sets (QOFSs), and the decision matrices include four dimensions: sentiment, feature, product and the store where the product is sold. These matrices are aggregated to obtain the final "sentiment" through a q-rung orthopair fuzzy interaction weighted Heronian mean operator. Following the same mechanism for computing sentiment scores and using the same sentiment dictionaries, an extension of this idea using interval-valued Pythagorean fuzzy sets (IVPFSs) can be found in [191].

In a previous study, all opinion scores were aggregated considering the moment when they were conveyed [192]. In this case, the feature polarity is affected not only by the opinion-word sentiments from a sentiment dictionary but also by the importance of the date/time when they were conveyed. An intuitionistic sentiment matrix was created for each time span t, and the values for each feature were intuitionistic fuzzy numbers (IFNs) measured as in previous studies (as the proportion between positive, negative and neutral values per aspect). The importance of each aspect was measured by calculating the intuitionistic fuzzy entropy [193], and all the matrices were aggregated by an operator called the dynamic intuitionistic fuzzy geometric average weighted aggregation (DDIFWGAA) operator, which considered the discrete time sequences of all the opinions. The result was the polarity toward a product.

A general framework for dealing with comparative expressions from Internet debates and a multigranular fuzzy linguistic method was presented in [194]. Each comparative sentence is associated with a strength degree used as a comparison measure. All the comparative sentences containing two features were compared to determine whether they contained positive, negative or similar words. To accomplish this requires three lists of words: one each for positive, negative, and similar preferences. From these comparative expressions, it is possible to assign different preference degrees depending on the words used and the strength degree of the expressions used. These values are used to create a preference matrix for each user that are then translated into fuzzy labels by a multigranular fuzzy linguistic mechanism. The resulting preference matrix is proposed for use in reaching consensus in GDM processes.

Many sentiment analysis models (SAMs) fail to detect neutrality; therefore, a model was proposed that integrated five SAMs and combined their output using an IOWA operator guided by a linguistic quantifier and a function measuring how close the outputs were to neutrality. Several experiments with varying quantifier parameters values were conducted to test this majority-based mechanism. The results showed that it outperformed models that use only single SAMs [195].

A two-stage MCDM approach to assess hotel quality was presented in [196]. The first step was performed by recruiting experts to assess the linguistic importance of SERVQUAL's features and match each hotel feature with the values in the SERVQUAL scale [197]. All the values were represented by 2-tuple ratings and aggregated to reach a consensus regarding the importance of each attribute. The second step computes the service quality by considering guests' opinions about the different hotel features. The opinions were extracted from reviews preprocessed by the Oracle text retrieval framework.[3] Finally, these values were aggregated by linguistic aggregation operators along with the importance values calculated in the previous step and the SERVQUAL scale ratings to rank the best hotels. An extension of the previous model was implemented in [198].

Morente el al. presented a GDM process applicable to different Internet tools such as social networks [199]. By processing texts (such as tweets that mention products and their alternatives), the associated sentiments can be computed by considering the numbers of positive or negative words from an initially predefined set of words. The resulting sentiment, measured in the range [0,1], can be transformed into a 2-tuple linguistic value that represents a user's preferences for a set of features from each product/alternative. This approach allows the alternatives to be ranked.

Another use of 2-tuple values was presented in [200] that represents an approach for acquiring a linguistic summary of datasets [201]. In this case, the dataset includes textual opinions preprocessed by Oracle Text to extract the main aspects. These aspects, along with other heterogeneous data, are represented by a fuzzy representation model based on semantic translation that transforms the information into fuzzy 2-tuple values to summarize the information of all the features from the dataset. An example was applied to hotel websites, in which the ratings were represented by the number of stars users assigned to each hotel aspect.

In [202], by preprocessing opinions to extract the main features of a product and using SentiWords [203] to compute the polarity of each word, the positivity and negativity of an aspect is measured by the mean of the polarity scores for every opinion word found. This value is used to compute the center of the TFNs representing the polarities of the aspects. The left and right sides are determined by a fixed value set to 0.25, and the intersection between them is used to determine the belief structures of evidential reasoning (ER), which are used to compute Wang's MCDM algorithm [204].

Most of the presented studies focus on fusing aspect sentiments and their goal is to rank products (hotels, doctors, cars, etc.) based on the overall opinion users hold about them using various hybrid approaches. The summary in Table 6 highlights the semantic resources employed and the fuzzy techniques applied.

[3] https://www.oracle.com/database/technologies/enterprise-edition.html.

6.4. Others

Note that other applications that combine sentiments and fuzzy logic can be found in the literature, some are even based on MCDM; nevertheless, they do not directly model feature sentiments using fuzzy logic, but characteristics such as user preferences in recommender systems, or related variables, such as user satisfaction, can be calculated by considering both sentiments and other factors. For instance, Ferrer et al. presented a recommender system based on product aspects [205]. The reviews are preprocessed by extracting aspects using a Wordnet-based clustering algorithm. The sentiments for each aspect are computed and normalized in the range [0,1] (0.5 represents a neutral sentiment) and used as fuzzy values to compute a preference or satisfaction degree. Users express their preferences and sentiments that reflect how much they like an aspect. When the preference is larger than the sentiment computed through the reviews, then a satisfaction degree can be assigned for each aspect. These degrees are aggregated using the product t-norm to determine the overall satisfaction degree, which is then used to rank all recommended products. In [206], another recommender system can be seen in which, a fuzzy string method is proposed to group every review into a classical aspect of a hotel: cleanliness, food, sleep quality, etc. The aspects are represented by the most recurrent terms and they are compared against all terms of a review by means of a fuzzy Levenshtein distance-based matching mechanism. Finally, all these aspects are then combined by an ensemble of different models of transfer learning using bidirectional encoder representations from transformers and random forest classifiers.

All the algorithms for feature detection shown in Section 3 have an associated accuracy ratio that reflects their performances and can be used to model features in a fuzzy way. Based on the idea of perceptual computing [207], Gupta et al. presented a mathematical approach for generating T2FS representations for an opinion word/concept/feature [208]. In this case, the sentiment a of an opinion word can be computed by any rating prediction algorithm, and the associated uncertainty α can be computed based on the algorithm's accuracy to rate an opinion word. The result is an interval $[a - a * \alpha, a + a * \alpha]$. From this initial interval, n random numbers can be generated to pair them to generate a final IT2FS.

Voice of the customer (VOC) is a process that records customers' input by capturing their needs and expectations regarding products and services [209]. Most of the previous studies in this field do not take user comments into account. Critical to quality (CTQ) factors, which relate high-level strategic focal points to project objectives, find a relation between the causes and effects of problems related to products/services. These factors are also treated as aspects that need to be detected (light, engine, cylinder) and categorized as positive or negative, depending on a manually developed list of positive and negative adjectives. A Sugeno-type fuzzy inference system is proposed, whose input is the positive or negative level of the different aspects. Finally, the output is the importance of every CTQ factor, which is used to measure the customer satisfaction.

Inspired by a previous study [210], the authors of [211] studied how emotional messages spread through an emotional network. First, they defined a fuzzy propagation model that matches the interactions between users and messages using a fuzzy relationship. Through this network, which contains messages classified only as positive or negative, it is easy to match the different diffusion patterns of emotional words and propagation patterns, that is, to investigate how an emotional message can cause other users to post more messages. The propagation patterns are represented by fuzzy sets that represent the peak message volume on the network over time.

Table 6
Summary of MCDM-based applications.

Article	Lexicon	Level	Fuzzy techniques
[165]	SentiWordNet	Sentence	T1FS and uninorm operator
[166]	Automatically-computed Lexicon	Sentence	T1FS and uninorm operator
[171]	AFINN	Product	HFSs
[172]	–	Product	IFSs and I-IFOWA operator
[173]	–	Product	Choquet integral
[7]	General Inquirer	Product	T2FNs
[175]	Manually collected	Product	T1FSs and T1OWA operator
[177]	Manually collected	Product	IFSs
[179,180]	HowNet	Product	IFSs
[181]	SentiTurkNet	Product	IVFSs
[183]	HowNet	Product	LINC and, mean and Bonferroni-based operators
[185]	R-project functions for sentiments	Product	PMVNNs
[188]	How-Net	Product	T1FSs
[190]	ECommerce Sentiment Dict[a] and a sentiment ontology	Product	QOFSs and weighted Heronian mean operator
[191]	ECommerce Sentiment Dict[a] and a sentiment ontology	Product	IVPFSs and IVPFHM operator
[192]	Manually created dictionary	Product	IFNs and DDIFWGAA
[194]	Predefined list of sentiment words	Product	Multigranular fuzzy linguistic mechanism
[196,198]	Manually collected	Product	2-tuple representation mechanism
[199]	Predefined list of sentiment words	Product	2-tuple representation mechanism
[200]	Manually collected	Product	2-tuple representation mechanism
[202]	SentiWords	Product	T1FSs

[a] https://github.com/zeitiempo/ECSD.

In [212], a system to assess human resource performance was proposed in which 18 input variables are obtained from text-based evaluations. This text was preprocessed by a lexicon-based approach to extract the rating from each evaluation. These ratings are then input to a fuzzy rule-based approach designed to assess employee performances.

The importance of an opinion can be calculated by a fuzzy rule-based system [213]. One of the input variables was the orientation of the opinion (positive or negative), which was calculated by a lexicon-based approach for the Portuguese language. The applied approach detects patterns consisting of pairs $\langle words, adj\rangle$ to compute the polarity. This variable is fuzzified by a membership function and used to compute the importance degree of an opinion. A comparative analysis of this technique and an ANN-based approach showed that, in general, the fuzzy approach outperformed the ANN-based approach [214].

A hype prediction model for Bollywood movies can be found in [215]. This fuzzy prediction system is based on actor/actress ratings and sentiments from tweets about the movies. The sentiments are computed by a lexicon-based probabilistic latent semantic analysis and fuzzified to form the input to a Mandani rule-based system that classifies the movies as hit, flop or average.

A fuzzy TOPSIS approach was used in [216] to rank different products based on user preferences over different product aspects/features. The preferences are represented by trapezoidal fuzzy numbers, which are aggregated along with feature weights computed over the historical data. After the fuzzy TOPSIS approach, the distance between all possible products is analyzed. In this step, recommendations are made by considering the sentiment associated with each product and adding up all sentiment word scores based on a manually created lexicon-biased by an influence factor related to the user who conveyed the opinion. In this case, the sentiments are directly modeled individually as in the previous section but are not the only factor considered when ranking the products.

A similar example appears in [217], which presents a decision-making mechanism for assessing websites. LDA is used to extract the aspects from opinions. On one hand, an LSTM classifier is trained to automatically compute sentiment polarity of the aspects extracted from the reviews. This polarity is refined through probabilistic linguistic term sets (PLTSs) by considering the degree of correlation between aspects. The result is a satisfaction degree expressed by 5 fuzzy labels ("very satisfied", "satisfied", "general", "unsatisfied", "very unsatisfied"). On the other hand, the causal relationships between aspects are determined by a FCM [107] for each website. An extended version of the extended Bonferroni mean operator was used to aggregate the attribute weights from the FCM and the satisfaction degree for a website to obtain an assessment degree for each website.

Through a textual debate between experts, it is possible to analyze the different aspects characterizing an alternative/product in a GDM process. Furthermore, the associated sentiments can also be computed by considering (similar to other papers) the number or positive or negative words from a set of predefined words. This analysis allows a query to be created containing user preferences; the more positive the opinion of an aspect is, the more important it is to the user. The constructed query is then used to search for the best alternatives for the given user in an ontology. A fuzzy ontology describing alternatives/products of the GDM process was implemented, and the relationships between concepts and entities (product-aspect) were represented by hesitant T2FSs. Finally, the most interesting alternatives for a user could be provided by aggregating the relationships between the preferred aspects of that user [218].

7. Open issues/challenges

After analyzing the main uses of fuzzy logic in different phases or application in opinion mining, the reader can realize that there are many gaps that are necessary to be covered. For instance, it is difficult to find studies in many recent research lines such as eXplainable AI (XAI), hatred detection, explicit and implicit feature detection, opinion search, opinion spam detection, sarcasm, among others.

Regarding the lexicon-based approaches, most of the used fuzzy lexicons are automatically generated, or the sentiment values are obtained from classical resources such as SentiWordNet and interpreted as possible fuzzy values but in a very simple manner. It is necessary to investigate new formal fuzzy definitions of sentimental lexicons which could help to apply fuzzy techniques, particularly on well-known domains for sentiment analysis: hotels, products, movies, etc. Apart from the formal definition, the quality of the resulting fuzzy lexicons from most automatic algorithms leaves much to be desired in many cases. Therefore, the automatic development of fuzzy domain-dependent lexicons still needs further investigation because the handcrafted development is a very tedious task.

Due to the existence of a great range of well-known and widely used aggregation operators, the applications developed at the aspect- or document-level have been extensively studied. Nevertheless, there is little work at the sentence-level and entity/word/concept-level. In the sense, the development of formal fuzzy lexicons, or new versions of the already existing resources, might help researchers to develop more applications in these other levels. The fuzzy formal representation should be independent from the language, which will make it more interesting to be applied to any lexicon, not only the classical ones in English, but also in other languages and dialects.

When it comes to MCDM and information fusion techniques, many approaches have been implemented paying special attention to interval-valued fuzzy sets, but others, such as 2-tuple fuzzy sets have not analyzed yet. Furthermore, the Choquet integral or the uninorms, some of the most widely used operators for fusing information in MCDM applications, have been little used for fusing information about sentiments or emotions.

Finally, as it can be seen, fuzzy logic, especially with respect to classification, have been used in collaboration with other algorithms to primarily model the processed information, for instance, using classical techniques such as FSVM or fuzzy clustering algorithms. Nonetheless, there are many proposals yet to be developed because of the hybridization of other approaches, paying especial to deep learning and ensemble methods, which are gaining a lot of interest at the moment.

8. Conclusions and future work

This article presented a systematic state-of-the-art review of research articles published in the past 10 years that involved different tasks and applications related to fuzzy logic applied to opinion mining. The review is organized into 3 broad dimensions related to opinion mining tasks: feature extraction and detection, sentiment classification and emotion analysis, and a dimension related to all the applications that involve both fuzzy logic and opinion mining.

From this survey, several conclusions can be drawn. Fuzzy logic has been exhaustively exploited as a technique useful both for representing sentiment-related information and for performing different sentiment analysis tasks. Fuzzy logic has been more broadly applied in sentiment classification than to any other task. Nevertheless, many studies do not use fuzzy logic in isolation; instead, they represent the information in a fuzzy way and use classical reasoning mechanisms such Mandani or TSK-based inference systems. They also tend to work with other techniques, such as SVMs and clustering algorithms. Thus, possibly the most exploited mechanism both for extracting features and for classifying opinions has been the fuzzy c-means algorithm, although it is worth noting that many studies are also based on rule-based systems. Note that most of the semantic approaches depend on ontologies, especially those designed for the domain in which they are applied, but the studies also rely on other dictionaries, such as SentiWordNet, to complete their information.

Regarding future work, although many scholars have conducted extended studies that apply fuzzy logic-based solutions to opinion mining tasks, many fields remain to be covered, for instance, subjectivity detection, explicit and implicit feature detection, multimodal sentiment analysis, cross-domain applications, cyberbullying, opinion search and summarization, among others.

Many articles emphasize the aggregation step because much work has been conducted on fuzzy operators in the past; nevertheless, it might be interesting to develop advanced representation models, especially for words and aspects, which are often represented by a value in the range [0,1] or by a TFN calculated by counting the number of positive or negative words in a sentence or opinions. The concept of neutrality is another forgotten concept that could be modeled in a fuzzy way to process opinions without a clear orientation. Moreover, while the dictionaries used in these studies are continuously being improved, they are not clearly fuzzified. This aspect might be particularly interesting in often-studied domains such as hotels, movies or products, in which, for example, a fuzzy ontology providing multigranular sentimental information could truly help to develop advanced solutions.

CRediT authorship contribution statement

Jesus Serrano-Guerrero: Conceptualization, Investigation, Writing - original draft. **Francisco P. Romero:** Investigation, Writing - review & editing, Funding acquisition. **Jose A. Olivas:** Supervision, Conceptualization, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This study was partially funded by FEDER, Spain and the State Research Agency (AEI), Spain of the Spanish Ministry of Economy and Competition under grant MERINET: TIN2016-76843-C4-2-R (AEI/FEDER, UE) and the Spanish Ministry of Sciences, Innovation and Universities under grant SAFER: PID2019-104735RB-C42.

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