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Negation Detection Techniques in Sentiment Analysis: A Survey

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Abstract

Negation is a linguistic phenomenon that can cause sentences to have their meanings reversed. It frequently inverts affirmative sentences into negative ones, affecting the polarity; therefore, the sentiment of the text also changes accordingly. Negation can be expressed differently, making it somewhat challenging to detect. As a result, detecting negation is critical for Sentiment Analysis (SA) system development and improvement and will increase classifier accuracy, but it also poses a significant conceptual and technical challenge. This paper aims to survey and gather the most recent research related to detecting negation in SA. Many researchers have worked and performed methods, including algorithmic, machine, and deep learning approaches such as Decision Tree (DT), Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Naive Bayesian (NB), Logistic Regression (LR), Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), Bidirectional Long Short-Term Memory (BiLSTM), and other hybrid methods such as rule-based and machine learning, lexicon and machine learning, machine learning, and deep learning. It addresses and tries to identify the gaps in the current studies, laying the foundation for future studies in this field.

Keywords: Machine learning, Natural language processing, Negation detection, Sentiment analysis (SA).

1. Introduction

Many Internet users utilize social media for a range of activities, such as connecting with friends, discovering new friends, and sharing user-generated material. On social media, users can use a variety of subjects to express and share their opinions on a range of topics. For instance, they can post comments, videos, photos, and other information to particular groups of people [1, 2, 3]. These opinions are expressed in various forms, including articles, reviews, forum postings, short comments, tweets, etc. Opinions are very important. Many companies and organizations have been interested in this data because they want to study people's opinions regarding political events, popular products, athletic events, films, and more [3, 4, 5]. These trends are opening up the era of SA. Determining the semantic orientation of a text—whether it is positive, negative, or neutral—is the main objective of the SA [6, 7]. This provides numerous advantages for companies, education, trade, health, and many other fields. Despite

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the wide use of SA applications, there is still room for improvement. Negation is one of the problems that continues to be a challenge in SA [8, 9, 10].

Negation has several forms, such as explicit with clear cues such as “not,” “no,” etc., implicit without negative words (e.g., “not very good” instead of inverting the polarity, it diminishes the polarity of good), and other restrained linguistic patterns [14]. Negations can take two forms at the highest structural level: morphological negations, where words are modified by either a prefix like non-, un-, etc. or a suffix like -less, etc., or syntactic negations, where explicit negation cues are used to invert a single word or a series of words [15, 16]. Additionally, fake negations, where the strings represent negations that have other usages not related to negation, and double negations, which are a nonstandard form where we use two negative particles for emphasis and sometimes it is used for positive, are two types of syntactic negations. Because different kinds of negation affect polarities differently, it is important to clearly distinguish between them when determining their effective scope [17, 18].

This paper presents some previous works about detecting negation in SA, their corpus, languages, domains, features, and techniques used for them in previous works also reviewed. In addition, this paper points out the gaps and directions for this field's future study. The rest of this paper is organized as follows: Section 2 presents the related work. Section 3 offers our discussion. Finally, Section 4 concludes the paper.

2. Related Work

Several methods, including algorithmic (rule-based) [14, 19], machine and deep learning approaches such as DT, SVM, KNN, NB, LR, ANNs, RNNs, BiLSTM [6, 15, 20, 21, 22, 23], or hybrids such as rule-based and machine learning, lexicon and machine learning, and machine learning and deep learning [13, 16, 20, 23], have been used to study the problem of negation detection. Most rule-based algorithms depend on simple rules made up of regular expressions and detect the scope of negation using dependency and parse trees. By contrast, supervised learning techniques use various classifiers to detect these phenomena. The studies and research in the most relevant works on negation detection are:

Farra et al. [6] studied Arabic text sentiment analysis at the sentence and document levels. Regarding classification, the sentence-level study investigates the grammatical approach and semantic orientation. In contrast, document-level research employs a novel method in which documents are dynamically split into chunks, and classification depends on the semantic contributions of various chunks to classify entire documents. This study suggests a hierarchical classification system that uses the result of the classifier at the sentence level as the entry to the classifier at the document level. Their work considers negation while attempting to capture the sentiment of Arabic text. This study just counted the frequency of negation phrases in the sentence while trying to build a semantic feature of the sentence based on the Arabic sentiment lexicon.

These features were employed, along with others of a similar nature, such as the frequency of positive, negative, and neutral words in each sentence. The authors do not consider the impact of negation words on other words. Their dataset uses 44 documents: 27 positives, 12 negatives, and 5 neutrals with known and correct class label phrases. SVM was used to enter the sentence features of 2238 sentences for document analysis. Using machine learning (SVM) as the classifier, they achieved an accuracy of 89.3 percent with their general sentence structure approach. Their study reveals that when the neutral class is excluded, dividing the texts into four chunks produces the best results, with an accuracy of 87.00%. However, the authors did not mention the list of commonly used negation words. Additionally, based on a simple representation, this method would not capture all of the sentence's semantics and syntax, which could help classify sentiment.

Al-Harbi [13] proposed a method for detecting and handling the negation issue in CA reviews to increase the efficacy of sentiment classification depending on machine learning. A sentiment lexicon, crafted rules, and linguistic knowledge were utilized in the proposed algorithm. Python 3.0 was used to develop the negation handling algorithm. He experimented with a 2,400-review, annotated dataset divided into two positive and negative categories. The data are reviews of various areas in Jordanian colloquial language and Modern Standard Arabic (MSA). In addition, he manually collected a list of the most typical negation terms used in the reviews. There are 50 terms on the negative list, including those used in the two types of Jordanian dialects and MSA. He constructed 14304 features by employing unigrams and a window length of five words immediately following a negation word. Four of the most widely used classifiers in SA were examined to see how the proposed algorithm affected them: SVM, KNN, NB, and LR. When his algorithm was used, he compared the classifiers to three baseline models with different approaches for determining the scope of the negation. When the proposed algorithm is used compared to the baselines, the experimental results demonstrate a positive impact on the classifiers' accuracy, precision, and recall; the SVM had the highest accuracy with 89.17%. However, his algorithm ignores implicit negation, which can negatively affect polarity classification. The use of intensifiers and diminishers, which can alter the polarity of words or phrases, is another issue that isn't addressed.

Using machine learning techniques, Mukherjee et al. [15] developed a new end-to-end SA approach to dealing with negations, including identifying and demarcating negations in online reviews. The approach implements a negation marking algorithm for explicit negation detection and performs experiments on SA like NB, SVM, ANNs, and RNNs on around 75,000 reviews gathered from Amazon Product Reviews, especially reviews of cell phones. Their approach focuses on various negations, including morphological negation, syntactical negation, double negation, and implicit negation. In the absence of negation marking, most explicit negations are lost during the pre-processing phase, implying that information that our approach can resolve is lost. Their research has led them to conclude that the sentiment classifier performs better when classifiers for text classification and negation identification are coupled. The experimental findings demonstrate the evaluation of the negation algorithm's impact on SA tasks. RNNs achieved the highest level of accuracy (95.67%) when paired with our negation marking processing. However, this approach's investigation of sentiment polarity detections did not consider double negations or implicit negations.

Using machine learning: Conditional Random Field (CRF), Councill et al. [16] provided a system for determining the scope of negation, specifically about a sentiment expressed in online reviews. Two kinds of negation were pointed out: morphological negation and syntactical negation. The scope of negation detection is restricted to syntactic structures within single sentences. Their collection provides a new corpus of negation created for English product reviews from the open web, consisting of 2111 phrases. There are 679 negated statements in this corpus, and every sentence was annotated manually to define its cues and scope. This system provides a lexicon of explicit negation cues, mentioning around 35 words as negation words. They used features like lowercase token strings, token parts of speech (PoS), and other features. Open-source CRF++ has been used to implement the CRF algorithm. The results of the experiments demonstrate that the suggested negation extraction system achieves 80.00% and 75.50% F1-scores, respectively, when evaluating the review corpus and the standard

BioScope corpus of negation. Their system, however, doesn't address implicit negations in their approach.

Hamouda et al. [18] made an effort to develop a sentiment analyzer for Arabic comments on Facebook news pages. The most recent news from the "Arab Region" and "Egypt" was selected. They collected 2400 comments from 220 posts, 800 of which were neutral, 800 of which were supportive, and 800 of which were attacking. Their experiments use various machine learning algorithms (DT, SVM, and NB) with different features to develop a sentiment analyzer. The number of negation words in the post, the number of negation words in the comment, and their relevance to the post are some examples of Arabic negation features. Their approach only contains five negation words, while there are numerous others. According to their methodology, the optimum result is obtained by including negative word features alongside the features of all words in the posts and comments. The experimental results indicate that SVM achieves the highest result of 73.40% in precision and recall. The general issue with this approach is that it might only apply to the posts and comments on Arabic news pages on Facebook, which is the domain they chose. With standard Arabic Sentiment Analysis (ASA), this might or might not work.

Kaddoura et al. [19] developed an approach to examining the impact of inverters on the SA of postings on social media in dialectal Arabic (DA) using syntactic and pattern-based features. Their system points to some of the difficulties that prevent employing directly negating terms as classification features, including fake inverters, implicit negation, and neutral targets. A study is done using a corpus of Facebook data consisting of 1000 posts collected from The Voice and Al-Arabiya News pages. The corpus's posts are categorized into three sets: spam, negative, and positive. Their approach uses Arabic negation words in MSA and DA, stating only eight negation words. Their approach highlights a few issues that can be misclassified because of ignoring negation in DA: inverters may be expressed in a variety of ways, even in the same dialect, and negation also occurs by using suffixes, prefixes, or as a separate word before the target. The findings show that treatment of negation may improve classification performance. The experimental results indicate that handling negation in the text raises the F1-score by 20%. Their approach doesn't, however, deal with odd negation, fake inverters, complex negation, or implicit negation.

Alemneh et al. [20] proposed a negation handling approach that enhances the SA of Amharic Facebook news comments. The presented negation handling approach combines the lexicon-based model and the character-n-gram-based machine learning model. Their dataset consists of 2,705 comments from Facebook News users, divided into two categories: positive and negative. Their approach develops a negation detection algorithm that returns true if a word contains a negation cue, either in the prefix, suffix, or in negation lists. The framework is implemented using the Python Scikit-Learn library. The proposed approaches are evaluated by measuring the accuracy of individuals and their combinations for Amharic text sentiment classification. This research reveals that combining a rule-based and a machine-learning method outperformed the best individual approaches. The training set's character-level bi- and tri-gram features are used to build the LR and NB models. The experimental findings demonstrate that the suggested technique (Negation Handling Approach (NH) + NB + LR) outperforms the best models and baselines by an accuracy of 98.00%. However, this approach has some errors in the SA of Amharic Facebook news comments. The method may not adequately capture the language-specific features that aid in determining the sentiment class of social media news comment text in Amharic.
Funkner et al. [21] used machine learning based on multi-class classification employed in

sentiment classification to detect negations in Russian medical reports. Their experiments were conducted with a dataset consisting of anonymized Russian, divided into three labels, consisting of 3434 electronic medical records (EMRs) of patients. The data consists of unstructured clinical texts about five diseases. Their method involves collecting a list of the most critical features of words and phrases that indicate the presence of disease in the anamnesis. The negation list contains 10 words and phrases. Their experiments focused on three of the classifiers used in SA: XGBoost, Random Forest (RF), and KNN, to evaluate how negation detection affects the predictive model's performance. According to the experimental findings, using a negation detector considerably improves the performances of XGBoost, RF, and KNN to predict surgery using only text features. The detector categorizes negations for five diseases and has an average F-score ranging between 81 and 93.

Jiménez-Zafra et al. [22] used a machine learning system to automatically identify negation cues and their scope in Spanish review texts. Their approach investigates whether accurate negation detection improves the outcomes of a SA system. Using the CRF classifier, the system works on the SFU Review SP-NEG dataset to detect negation cues and their scopes. There are 400 product reviews in the SFU Review SP-NEG Spanish dataset, with 25 positive and 25 negative reviews from 8 domains. Their method mentions that negation cues in this dataset may be simple, contiguous, or non-contiguous. In addition, their system uses 31 features for detecting negation cues and 24 features for detecting scope. Their method used the Semantic Orientation CALculator (SO-CAL) without negation as baselines and SO-CAL with built-in negation. The findings demonstrate that accurate recognition of cues and scopes is crucial for the sentiment classification task and show that simple negation strategies are not enough for sentiment detection. The cue detection module has a score of 92.70% and a good recall of 82.09%. On the other hand, the scope identification module is 90.77%, but its recall of only 63.64%, which is not very high. However, a system may be appropriate only to detect a few negatives because it can occasionally produce an extremely high negative score.

Mahany et al. [23] introduced the issue of negation detection in texts and its importance for Arabic Natural Language Processing (ANLP) tasks such as SA. In an effort to address this shortcoming in the texts of MSA and Classical Arabic (CA), an experiment is carried out on a dataset of data that has been manually annotated with negation. Their corpus consists of two sub-corpora, each of which has 3,000 sentences, and was compiled from the King Saud University Corpus of Classical Arabic (KSUCCA) and Wikipedia. The negation cues in the entire corpus have only six negative particles. The features’ vector size (d), window size (w), and minimum word count were utilized to construct the word embedding models. Their work investigates various model architectures using supervised machine learning and deep learning algorithms to address the issue of negation detection in Arabic texts. The Word2Vec toolkit will build a supervised neural network model by transforming the textual corpus into a list of input and output words. Their system relies on Word2Vec and FastText word embedding, with the SVM and BiLSTM as two distinct classifiers. SVM+Word2Vec is regarded as the baseline system for comparison with their FastText+BiLSTM system. The method is implemented using the Python language. According to the experimental results, their negation scope detection system outperformed the baseline with an F1-score of 89.00% and an accuracy of 93.00%. Although they discuss several types of negation, including implicit negation and fake inverters, they do not explain how to handle them in their proposed system.

3. Discussion

Negation is an important phenomenon that can cause sentences to have their meanings reversed. This section discusses the negation detection techniques in SA in 10 papers. There are two subsections in this section: the first is dedicated to presenting the corpora annotated with negation, while the second section offers methods and techniques from the existing works related to automatic negation detection.

3.1 Corpora

The annotated corpus with negation varies in language, domain, size, and annotated span level (cue and scope). Cue is the most crucial component because it affects the other

Table 1: A summary of the existing works related to corpora.

Ref.	Corpus	Lang.	Domain	Size
[6]	Movie Review	Arabic	Review	44 documents (2238 sentences)
[13]	Review	Arabic (MSA, Colloquial Jordanian)	Review	1200
[15]	Product Review	English	Review	75000
[16]	Product Review and BioScope	English	Review and Biomedical	2111
[18]	Facebook Comment	Arabic	Comment	2400
[19]	Facebook Comment	Arabic (MSA, DA)	Comment	1000
[20]	Facebook Comment	Amharic	Comment	2705
[21]	EMR	Russian	Record	3434
[22]	SFU Review	Spanish	Review	400
[23]	KSUCCA and Wikipedia Sentence	Arabic (MSA, CA)	KSUCCA and Wikipedia	3000

components and is necessary for handling negation. Negation involves several tasks, including cue detection and scope identification. As shown in Table 1, they cover texts extracted from various domains: reviews, biomedical, comments, and others.

The previous studies have been addressed in five languages: Arabic, English, Amharic, Russian, and Spanish. In addition, several text sources have been utilized, with the researchers in this field appearing to see reviews and comments almost exclusively as corpora for their work on negation detection. This could suggest an emphasis on social media. This could indicate an emphasis on social media. Additionally, there is a critical variation in the size of the corpora utilized in the different studies. Most studies employ just one kind of data, although there have been a few instances where several types of data have been merged.

Analyzing the results in Table 1, it was found:

- There is a lack of work in negation detection, and almost all authors used their corpus. They explained this by the lack of a corpus.
- Regarding language, most of the studies in this area have concentrated on non-Arabic languages; Arabic in MSA and DA requires additional study and research.
- The numerous studies on negation detection employed the small size of the corpus; ideally, a training corpus needs to be large for a system to be able to learn.
- There is no research on negation detection using all the different negation words.
- The majority of work in negativity detection is in the news or business/film review fields. Different kinds of data could also be added.

• There is still no published study on negation detection covering the different types of negation.

3.2 Methods and Techniques

Numerous systems for negation detection have been developed, ranging from algorithmic (rule-based) [14, 19] to machine and deep learning approaches such as DT, SVM, KNN, NB, LR, ANNs, RNNs, and BiLSTM [6, 15, 20, 21, 22, 23], or hybrids such as rule-based and machine learning, lexicon and machine learning, and machine learning and deep learning [13, 16, 20, 23]. Figure 1 and Table 2 summarize the studies above that have been done on negation detection. An overview of the model applied to negation detection is shown in Figure 1. It is evident from Figure 1 that machine learning has a dominant position over other techniques. Table 2 illustrates the features and model used in negation detection, the software used, the best result obtained, and describes the gaps in the previous studies.

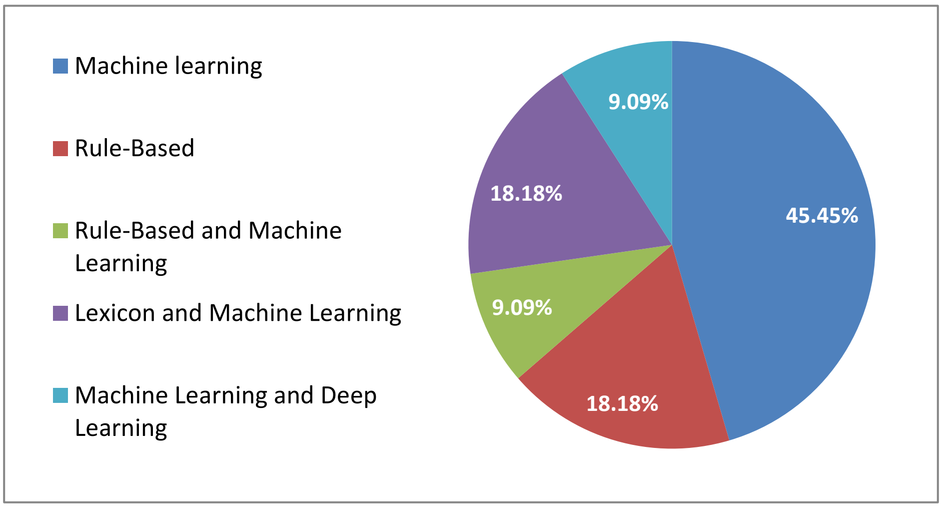

Figure 1: Automatic negation detection studies by used model

Analyzing the results in Figure 1 and Table 2, it was found:

• The authors used numerous features, like lexical features, character n-grams, syntactic features, etc.

• Most studies use the SVM, NB, and KNN to classify negation detection.

• The authors used different software to implement their algorithms.

• The authors used different types of measures to test their classifiers. Almost all of them used recall, precision, and F1-Score.

• There are differences between the classifiers in accuracy, error rate, and time taken to build the classification.

• Poor handling of fake inverters and implicit negation haven't been addressed.

4. Conclusion

This paper presented an overview of working on negation detection. This study summarizes various datasets such as reviews, BioScope, comments, EMR, KSUCCA, and Wikipedia sentences used by them in their work. In addition, it offers different negation detection approaches, including algorithmic, machine, and deep learning approaches; other hybrid methods that apply in a range of languages, domains, and results; and present limitations. Their primary tasks have focused on identifying the negation cues and their scope by applying rule-based approaches to machine-learning techniques. As for future work, we intend to propose and develop an automatic negation detection approach for Arabic SA, using a machine-learning technique to solve some of the existing problems in the Arabic negation detection approaches highlighted in this survey as well as to obtain an optimal system for

Arabic negation detection. In addition, we intend to investigate the use of lexicons and new additional features to better distinguish between negated and non-negated text

Table 2: A summary of the existing works related to automatic negation detection.

Ref.	Features	Model Used	Software	Best Result	Gaps
[6]	Semantic	Machine learning (J48 DT and SVM)		Accuracy SVM 87.00%	The authors did not mention the list of used negation words. Based on a simple representation, this method wouldn't catch all of the semantics and syntax of the sentence, which could help classify sentiment.
[13]	Syntactic	Rule-Based and Machine Learning (SVM, NB, KNN, and LR)	Python 3.0, RapidMiner	F1-Score SVM 89.00%	Implicit negation, which can also have a negative impact on polarity classification, is ignored by the algorithm. The proposed method doesn't consider how intensifiers and diminishers are used because they can alter the polarity of words or phrases.
[15]	Syntactic	Machine Learning (NB, SVM, ANN, and RNN)		Accuracy RNN 95.67%	In their investigation of sentiment polarity detections, this method did not take into account implicit negations and double negations. Experiments were based on Amazon Product Reviews, specifically on cell phones, and not tested in the general domain.
[16]	Syntactic, Lexical	Lexicon and Machine Learning (CRF)	CRF++	F1-Score 80.00%	Only explicit negations were considered.
[18]	Syntactic	Machine Learning (DT, SVM, and NB)		F1-Score SVM 73.40%	They used only 5 different negation words. Their suggested method might only work for comments and posts on Arab Facebook news pages, and may or may not work with regular ASA.
[19]	Syntactic, Pattern	Rule-Based		F1-Score 93.00%	The work doesn't deal with odd negation, fake inverters, complex negation, and implicit negation.
[20]	Lexical, Character N-gram	Lexicon and Machine Learning (LR, NB)	Python	F1-Score NH+NB+LR 98.00%	This approach has some the number of errors in the SA of Facebook news comments in Amharic. Experiments were based on Facebook news users' comments collected from the GOAC and not tested on the general domain.
[21]	Syntactic	Machine Learning (XGBoost, RF, and KNN)		F1-Score RF 93.00%	The method was tested using the EMRs of patients with ACS and needs to be tested for general domain corpora.
[22]	Syntactic	Machine Learning (CRF)	SO-CAL	F1-Score 75.00%	A small corpus of 400 product reviews. A system may be appropriate only to detect a few negations.
[23]	Word Embedding	Machine Learning (SVM) and Deep Learning (BiLSTM)	Python	F1-Score FastText+ BiLSTM 89.00%	Only two genres (KSUCCA and Wikipedia) have been considered, and further testing on other genres is required. The negation cues in the entire corpus have only 6 negative particles. They didn't explain how to deal with implicit negation and fake inverters through their proposed system.

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