International Journal of Applied Science and Engineering

Negation detection techniques in sentiment analysis: A survey

Ahmed S. Abuhammad[1,2*], Mahmoud A. Ahmed[3]

[1] *Department of Information Technology, University of the Holy Quran and Taseel of Science, Wad Madani, Sudan*
[2] *Department of Computer Science and Information Technology, University College of Science and Technology, Khan Younis, Palestine*
[3] *Department of Computer Science, University of Khartoum, Khartoum, Sudan*

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. In addition, this paper points out the gaps and future research directions in this area.

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

OPEN ACCESS

Received: November 24, 2022
Revised: January 16, 2023
Accepted: February 4, 2023

Corresponding Author:
Ahmed S. Abuhammad
asj.hammad@ucst.edu.ps

Publisher:
Chaoyang University of Technology
ISSN: 1727-2394 (Print)
ISSN: 1727-7841 (Online)

1. INTRODUCTION

Many Internet users utilize social media for various 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, movies, images, and other content to particular groups of persons (Tungthamthiti et al., 2016). These opinions are expressed in various forms, including articles, reviews, forum postings, short comments, tweets, etc. Opinions are critical. Numerous businesses and organizations were interested in this data because they wanted to study people's opinions regarding political events, famous goods, athletic events, films, and more (Bouazizi et al., 2002). These trends open the era of SA. Determining a text's semantic orientation (positive, negative, or neutral) is the main objective of SA (Farra et al., 2010). This provides numerous advantages for companies, education, trade, health, and other fields. Despite the wide use of SA applications, there is still room for improvement. Negation is one of the problems still challenging in SA (Mohammad et al., 2016; Hussein et al., 2018; Eremyan et al., 2021).

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 is "The absence or opposite of something actual or positive" in the online Oxford and Collins dictionary. Negation flips the polarity of sentiment in the general area of SA. As a result, the classification of polarity is incorrect. As a result, detecting negation is critical for SA systems development and refinement and will increase classifier accuracy. Still, it is, at the same time, a significant conceptual and technical challenge (Hussein et al., 2018; Al-Harbi, 2020; Eremyan et al., 2021). This led to an interest in the research problem of automatic negation detection. Automatic negation detection refers to computational methods that predict whether or not a given text is negative. Due to the various ways that negation can be expressed, this problem is complex.

Negation has several forms, such as explicit (with clear cues such as not, no, etc.), implicit (without negative words), diminutives, and other restrained linguistic patterns (Farooq et al., 2017). Negations can take two forms at the highest structural level: morphological negations or syntactic negation (Councill et al., 2021; Mukherjee et al., 2021). Additionally, fake negations where the strings represent negations that have other usages unrelated to negation and double negations are two types of syntactic negations. Because different kinds of negation affect polarities differently, it is essential to clearly distinguish between them when determining their adequate scope (Hamouda et al., 2013; Al-Salmi, 2019).

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 literature review. Section 3 offers our discussion. Finally, Section 4 concludes the paper.

2. LITERATURE SURVEY

Several methods, including algorithmic (rule-based), machine and deep learning approaches such as DT, SVM, KNN, NB, LR, ANNs, RNNs, BiLSTM, or hybrids such as rule-based and machine learning, lexicon and machine learning, machine learning and deep learning, 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 of the most relevant works on negation detection are:

Farra et al. (2010) 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 pick up the Arabic text's sentiment. 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 neutral) with known and correct class label phrases. SVM were used to enter the sentence features of 2238 sentences for document analysis. Using machine learning: SVM as the classifier, they achieved an accuracy of 89.30% with their general sentence structure approach. Their study discovers that when the neutral class is excluded, dividing the texts into 4 chunks produces the best results, with an accuracy of 87.00%. However, the authors did not mention the list of 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 (2020) 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 2400-review annotated dataset divided into two positive and negative categories. The data are reviews about 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 5 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 3 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. (2021) 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 SA of 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. (2010) 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 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 string, token Part of Speech (PoS), and other features. CRF++ open-source has been used to implement the CRF algorithm. The results of the experiments demonstrate that the suggested negation extraction system achieves 80.0% and 75.50% F1-scores, respectively, when evaluating the reviews corpus and the standard BioScope corpus of negation. Their system doesn't, however, address implicit negations in their approach.

Hamouda et al. (2013) 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 with a post are some examples of Arabic negation features. Their approach only contains 5 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, this might or might not work (ASA).

Kaddoura et al. (2021) developed an approach to examining the impact of inverters on 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 of 1000 posts collected from The Voice and Al-Arabiya News pages. The corpus's posts are categorized into 3 sets: spam, negative, and positive. Their approach uses Arabic negation words in MSA and DA, stating only 8 negation words. Their approach highlights a few issues which 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, and implicit negation.

Alemneh et al. (2020) 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 2705 comments from Facebook news users, divided into 2 categories (positive and negative). Their approach develops a negation detection algorithm that returns true if a word contains a negation cue, either prefix, suffix, or in negation lists. The framework is implemented using the python sci-kit learn library. The proposed approaches are evaluated by measuring the accuracy of individual 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 char level bi-gram 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. (2020) used machine learning based on multi-class classification employed in sentiment classification to detect negations in Russian medical reports. Their experiments conduct with a dataset consisting of anonymized Russian language divided into three labels, consisting of 3434 Electronic Medical Records (EMRs) of patients. The data consists of unstructured clinical texts about 5 diseases. Their method collects 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 conduct on 3 of the classifiers used in SA, XGBoost, Random Forest (RF), and KNN to evaluate how the 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 5 diseases and has an average F-score ranging between 81.00% and 93.00%.

Jiménez-Zafra et al. (2020) used a machine learning system to automatically identify negation cues and their scope in Spanish review texts. Their approach investigates if 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 is 92.70% and with a good recall of 82.09%. On the other hand, the scope identification module is 90.77%, but its recall is only 63.64%, which is not very high. However, a system may be appropriate only to detect a few negations because it can occasionally produce an extremely high negative score.

Mahany et al. (2021) 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 King Saud University Corpus of Classical Arabic (KSUCCA) and Wikipedia. The negation cues in the entire corpus have only 6 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 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 2 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 through 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 among 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 of the existing works related to automatic negation detection.

3.1 Corpora

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 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 5 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 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 results in Table 1 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 different negation words.

- The majority of work in negation detection is in the news or business/film review fields. Different kinds of data also could 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), machine and deep learning approaches such as DT, SVM, KNN, NB, LR, ANNs, RNNs, BiLSTM, or hybrids such as rule-based and machine learning, lexicon and machine learning, machine learning and deep learning. Fig. 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 Fig. 1. It is evident from Fig. 1 that machine learning has dominant 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. Analyzing results in Fig. 1 and Table 2 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 the 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 the accuracy, error rate, and time taken to build the classification.
- Poor handling of fake inverters and implicit negation haven't been addressed.

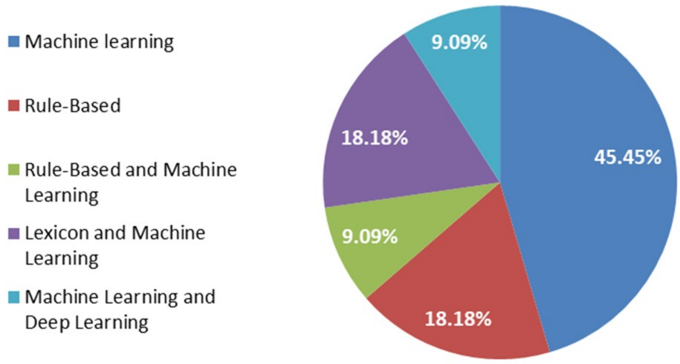

Fig. 1. Automatic negation detection studies by used model

4. CONCLUSION

This paper presented an overview of working on negation detection. This study summarizes various datasets such as reviews, BioScope, comments, EMR, KSUCCA, Wikipedia sentence used by them in their work. In addition offers the different negation detection approaches including algorithmic, machine, and deep learning approaches, other hybrid methods that apply in a range of languages, domains, and results, as well as 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 as 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 1. A summary of the existing works related to corpora

Reference	Corpus	Language	Domain	Size
Farra et al. (2010)	Movie Review	Arabic	Review	44 documents (2238 sentences)
Al-Harbi (2020)	Review	Arabic (MSA, Colloquial Jordanian)	Review	1200
Mukherjee et al. (2021)	Product Review	English	Review	75000
Councill et al. (2010)	Product Review and BioScope	English	Review and Biomedical	2111
Hamouda et al. (2013)	Facebook Comment	Arabic	Comment	2400
Kaddoura et al. (2021)	Facebook Comment	Arabic (MSA, DA)	Comment	1000
Alemneh et al. (2020)	Facebook Comment	Amharic	Comment	2705
Funkner et al. (2020)	EMR	Russian	Record	3434
Jiménez-Zafra et al. (2020)	SFU Review	Spanish	Review	400
Mahany et al. (2021)	KSUCCA and Wikipedia Sentence	Arabic (MSA, CA)	KSUCCA and Wikipedia	3000

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

Reference	Features	Model Used	Software	Best Result	Gaps
Farra et al. (2010)	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.
Al-Harbi (2020)	Syntactic	Rule-Based and Machine Learning (SVM, NB, KNN, and LR)	Python 3.0, Rapid Miner	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.
Mukherjee et al. (2021)	Syntactic	Machine Learning (NB, SVM, ANNs, and RNNs)		Accuracy RNNs 95.67%	In their investigation of sentiment polarity detections, this method did not consider implicit negations and double negations. Experiments were based on Amazon Product Reviews, specifically on cell phones, and not tested in the general domain.
Councill et al. (2010)	Syntactic, Lexical	Lexicon and Machine Learning (CRF)	CRF++	F1-Score 80.00%	Only explicit negations were considered.
Hamouda et al. (2013)	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 news pages on Facebook and may or may not work with ordinary ASA.
Kaddoura et al. (2021)	Syntactic, Pattern	Rule-Based		F1-Score 93.00%	The work doesn't deal with odd negation, fake inverters, complex negation, and implicit negation.
Alemneh et al. (2020)	Lexical, Character N-gram	Lexicon and Machine Learning (LR, NB)	Python	F1-Score NH+NB+LR 98.00%	This approach has some the amount 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.
Funkner et al. (2020)	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.
Jiménez-Zafra et al. (2020)	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.
Mahany et al. (2021)	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.

REFERENCES

Alemneh, G., Rauber, A., Atnafu, S. 2020. Negation handling for amharic sentiment classification. The 4th Widening Natural Language Processing Workshop – Workshop Proceedings, Seattle, WA, USA, 4–6.

Al-Ghazalli, M. 2013. Translation assessment of arabic implicit negation into English. International Journal of English Linguistics, 3.

Al-Harbi, O. 2020. Negation handling in machine learning-based sentiment classification for colloquial arabic. International Journal of Operations Research and Information Systems, 11.

Al-Salmi, A. 2019. The negation system in Arabic and English language. Bachelor's Thesis, KSA.

Bouazizi, M., Ohtsuki, T. 2002. A pattern-based approach for sarcasm detection on Twitter. IEEE Access, 4, 5477–5488.

Collins dictionary. Definition of Negation. Retrieved 2021-11-01 from https://www.collinsdictionary.com/dictionary/english/negation.

Councill, I.G., McDonald, R., Velikovich, L. 2010. What's great and what's not: Learning to classify the scope of negation for improved sentiment analysis. Proceedings in the Workshop on Negation and Speculation in Natural Language Processing, NeSp- NLP 7810. Association for Computational Linguistics, Stroudsburg, PA, USA, 51–59.

Eremyan, R. Four Pitfalls of Sentiment Analysis Accuracy. Retrieved 2021-11-01 from https://www.toptal.com/deep-learning/4-sentiment-analysis-accuracy-traps

Farooq, U., Mansoor, A., Nongaillard, A., Ouzrout, Y., Qadir, M. 2017. Negation handling in sentiment analysis at sentence level. Journal of Computers, 12, 470–478.

Farra, N., Challita, E., R., Assi, A., Hajj, H. 2010. Sentence-level and document-level sentiment mining for Arabic texts. In Data Mining Workshops (ICDMW) – IEEE International Conference Proceedings, 1114–1119.

Funkner, A., Balabaeva, K., Kovalchuk, S. 2020. Negation detection for clinical text mining in Russian. Studies in Health Technology and Informatics, 270, 43–47.

Jiménez-Zafra, S. M., Cruz-Díaz, N. P., Taboada, M., Martín-Valdivia, M. T. 2020, Negation detection for sentiment analysis: A case study in Spanish, Natural Language Engineering, 27, 2, 225–248.

Hamouda, A.E.D.A., El-Taher, F.E.Z. 2013. Sentiment analyzer for Arabic comments system. International Journal of Advanced Computer Science and Applications (IJACSA), 4, 99–103.

Hussein, D. 2018. A survey on sentiment analysis challenges. The Journal of King Saud University - Engineering Sciences, 30, 330–338.

Kaddoura, S., Itani, M., Roast, C. 2021. Analyzing the effect of negation in sentiment polarity of Facebook dialectal Arabic Text. Journal of Applied Sciences, 11, 1–13.

Mahany, A., Fouad, M.M., Aloraini, A., Khaled, H., Nawaz, R., Aljohani, N.R., Ghoniemy, S. 2021. Supervised learning for negation scope detection in Arabic texts. IEEE 10th International Conference on Intelligent Computing and Information Systems (ICICIS)– Conference Proceedings, Cairo, Egypt, 177–182.

Mohammad, S. 2016. A practical guide to sentiment annotation: Challenges and solutions. The 7th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis– Conference Proceedings, San Diego, California, 174–179.

Mukherjee, P., Badr, Y., Doppalapui, S., Srinivasan, S., Sangwan, R., Sharma, R. 2021. Effect of negation in sentences on sentiment analysis and polarity detection. Journal of the Procedia Computer Science, 185, 370–379.

Oxford dictionary. Definition of Negation. Retrieved 2021-12-01 from https://www.lexico.com/definition/negation

Stanford Encyclopedia of Philosophy. Negation. Retrieved 2021-11-01 from https://plato.stanford.edu/entries/negation/

Tungthamthiti, P., Shirai, K., Mohd, M. 2016. Recognition of sarcasm in microplogging based on sentiment analysis and coherence identification. Journal of Natural Language Processing, 23, 383–405.