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Negation handling for sentiment analysis task: approaches and performance analysis

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ABSTRACT

Negation plays an essential role in sentiment analysis within natural language processing (NLP). Its integration involves two key aspects: identifying the scope of negation and incorporating this information into the sentiment model. Before delving into scope detection, the specific negation cue must be identified, with explicit and implicit negation cues being the two main types. Various methodologies, such as rule-based, machine learning, and hybrid approaches, address the negation scope detection challenge. Strategies for leveraging negation information in sentiment models encompass heuristic polarity modification, feature space augmentation, end-to-end approach, and hierarchical multi-task learning. Notably, there is a need for more studies addressing implicit negation cue detection, even within the state-of-the-art bidirectional encoder representation for transformers (BERT) approach. Some studies have employed reinforcement learning and hybrid techniques to address the implicit negation problem. Further exploration, particularly through a hybrid and multi-task learning approach, is warranted to make potential contributions to the nuanced challenges of handling negation in sentiment analysis, especially in complex sentence structures.

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1. INTRODUCTION

Sentiment analysis (SA) can be applied to recommendation systems, market research, criminal communication detection, political opinion measurement, affective computing, and students feedback [1]–[4]. SA is a part of natural language processing (NLP), which aims to extract sentiments and opinions from text [5], [6]. Sentiment analysis can be considered text classification [7]–[9] because the process includes classifying whether a text has a positive or negative sentiment [10]. Sentiment analysis may seem easy, but it includes many problems in the NLP subtasks [10]. One of the problems in NLP sub-tasks is negation.

Negation is a linguistic phenomenon that often influences the sentiment analysis task [11]. In sentiment analysis based on a lexicon-based approach, researchers first try to model negation with simple heuristics, such as reversing the value or modifying the sentiment score from the sentiment lexicon [12]. In the literature review conducted by Hussein [13], it was stated that negation is the most crucial challenge in sentiment analysis and has the most significant impact, whether from structured, semi-structured, or unstructured reviews. Negation in natural language is a linguistic phenomenon that reverses the meaning of a sentence. Negation turns the affirmative sentence into a negative, which affects the polarity of the words so that the sentiment expressed in the text also changes [14]. Negation handling (NH) is an essential sub-task in sentiment analysis in NLP and is considered one of the most challenging problems in NLP in opinion mining. Negation handling in NLP is related to the automatic detection of polarity shifts in opinion sentences expressed in natural language text format.

Based on previous research, this article presents an overview of various techniques for negation handling in sentiment analysis tasks. This article aims to gain insight into the various approaches, performance analysis, and challenges in negation handling for sentiment analysis. Additionally, a comparative analysis is conducted to discern the strengths and limitations of the identified approaches, fostering a comprehensive perspective on the utility and adaptability of different negation handling methods within the context of sentiment analysis tasks.

2. NEGATION HANDLING IN SENTIMENT ANALYSIS

Negation handling is a low-level sub-task in sentiment analysis to determine the negation scope and incorporate the sentiment model's negation information. In general, the negation handling process in SA is shown in Figure 1. Before the negation scope is determined, the negation cue must be identified first. A negation cue is a marker that indicates changes in the meaning of a statement in the context of the sentence [15]. Understanding and identifying negation cues is crucial because it has significant implications for processing and understanding text. In the linguistic scope, negation cues can be classified into two main categories: explicit negation and implicit negation [15], [16]. Explicit negation shows the negation cue explicitly in the sentence by using words like "not", which indicates the presence of negation, for example, in the sentence "This movie is not good".

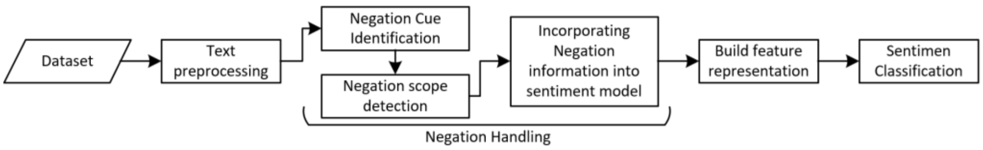

Figure 1. Generic sentiment analysis process that includes negation handling

On the other hand, implicit negation leads to conveying a negation that implicitly reverses the meaning of the sentence without any explicit words that directly state the negation. For example, in the sentence "The actor did a great job in his last movie; it was the first and last time", there is a reversal of meaning without any explicit words indicating negation [15]. Figure 2 illustrates the separation of explicit negation based on its categories, providing a more detailed picture of the characteristics and classification of negation in written language.

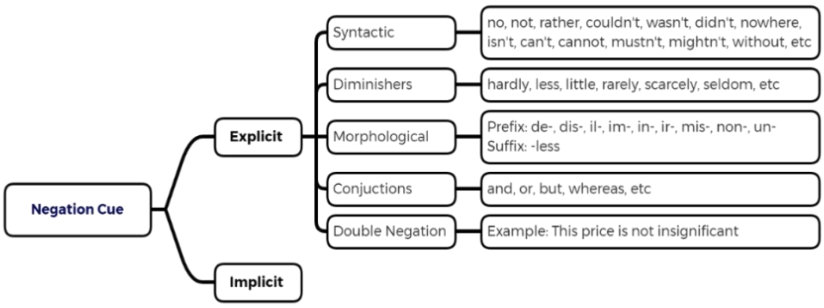

Figure 2. Types of negation cue

3. APPROACHES AND RELATED WORKS OF NEGATION HANDLING IN SA

3.1. Literature survey of negation scope detection

Negation scope detection (NSD) in several studies is also called negation scope resolution [17]. Which is related to determining the scope or coverage in a sentence affected by negation. Several approaches have been proposed to handle this task, including the rule-based approach, which relies on linguistic rules:

the machine learning approach, which utilizes statistical models for pattern recognition; and the hybrid approach, which combines elements of the previous approaches following the framework in Figure 3.

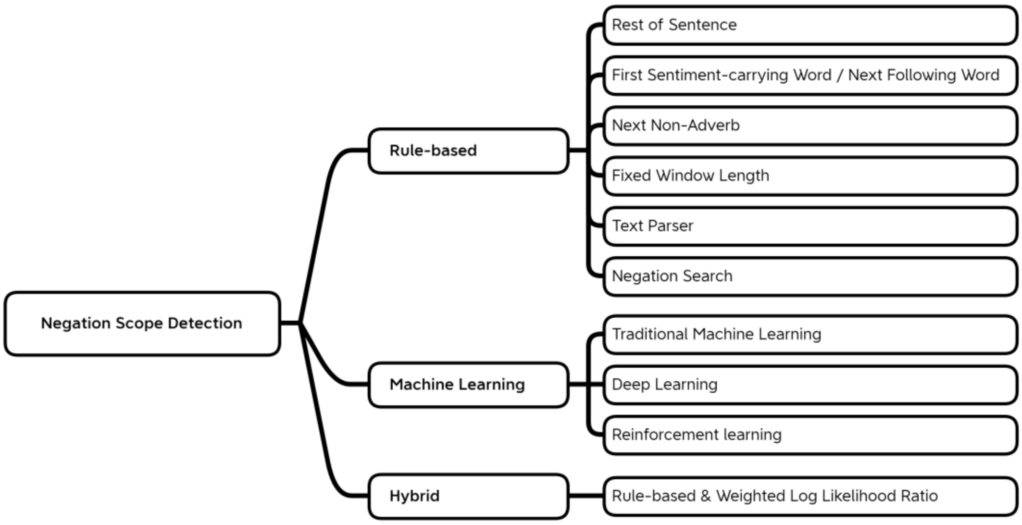

Figure 3. Negation scope detection approach

3.1.1. Rule-based approach

A rule-based approach is an approach that determines the scope of negation based on specific rules that have been defined. This approach has been proven successful in various fields and often does not require additional adjustments [18]. The negation cue in a sentence can be detected using a predefined lexicon. In the rule-based approach, some rules assume that the meaning of each word in a sentence is reversed (rest of sentence approach) [19]–[24], while other rules assume that the negation signal is in the following words (first sentiment-carrying word approach) [18], [21], [22]. Rule-based approaches can also include syntactic information to determine the subject or object in a sentence [25]–[28]. However, for implicit negation cue problems, this approach is not very practical because it is very dependent on certain specific domains [15]. Because this approach determines the scope of negation only by relying on the rules that have been created, the dependence on labeled data is not taken into account.

a. Rest of sentence (RoS): assumes that all words in a sentence containing a negation cue are within the scope of negation. This approach has been used by several previous researchers [18]–[24]. In research [21], [22], [24], this approach has lower accuracy performance compared to other rule-based approaches in the sentiment analysis task. However, this approach is still better compared to not using negation handling at all for the sentiment analysis task [19], [20], [29].
b. Negation search (NS): is an approach proposed by [18] that consists of backward and forward negation search. This approach is similar to RoS, but only words in certain POS tags (adjectives and adverbs) are stated to be included in the scope. Their research aims to produce a dictionary, or what is usually called a sentiment lexicon, that is more robust than existing dictionaries. Based on research results, it is proven that the resulting dictionary has better performance than other experimented approaches.
c. First sentiment-carrying word (FSW): the negation scope in this approach only lies in a word after the negation cue. In the sentiment analysis task, research [21], [22] compared the accuracy performance of several rule-based approaches for negation. The research [22] shows that the best accuracy performance is obtained using the FSW approach for the negation scope. Salmony and Faridi [22] mentioned implicit negation several times, but no solution was offered. In research [21], the accuracy performance of this approach ranks second among several compared approaches.
d. Next non-adverb (NNA): only takes words after the negation cue that are not included in the group of words with the adverb type. This approach assumes that the adverb after the negation cue is not included in the negation scope because it is an adverb itself [21]. The results in research [21], which focuses on comparing several rule-based methods for negation scope detection, show that this approach is better than RoS. However, in some cases, this approach is no better than the FSW and fixed window length approach. Another study [24] that used this approach obtained the same results as previous research, namely that the next non-adverb was better when compared to RoS.

e. Fixed window length (FWL): among other rule-based approaches, this approach has the best accuracy performance when applied to the sentiment analysis task [21]. FWL is a method used to determine the negation scope in a sentence. In this approach, several words that are after or around the negation cue are considered to be within the scope of negation. This method involves determining the window size. For example, if the window is set to 2, the two words after the negation keyword will be considered in scope. Experimental results in research [21] show that the performance of the FWL method with a window size of 2 is better when compared to the RoS, FSW, and NNA approaches. Other research [30] uses this approach to build a Sentiment Lexicon by considering negation; experimental results show that considering negation in building a sentiment lexicon can improve the performance of the F-measure and other performance metrics. This research alludes to implicit negation cues but is misinterpreted where implicit negation is considered morphological negation. Another research [31] used FWL for negation scope detection with different window sizes and predefined negation cues. When the negation cue is only 'not,' there is no difference in accuracy results for several test scenarios. Various accuracy results were produced when using no, not, rather, and hardly as negation cues. The best performance is obtained using the predefined negation cue with window sizes 2 and 4.
f. Text parser (TP): determining the scope of negation in several previous studies [26]–[28] used text parser. TP involves analyzing grammatical structures in sentences to determine the relationships between words. Text parser for negation scope works by determining words related to the words included in the negation cue in a sentence. In research [26], the text parser used was Xerox incremental parser [32]. Meanwhile, research [27], [28] uses the dependency parse tree to determine the relationship between words in a sentence based on their structure. Research [27], [28] carried out a sentiment analysis task that included negation handling and word sense disambiguation (WSD) tasks to get good accuracy performance. The approach to negation scope detection does not work well when there are word intensifiers after the negation cue. However, this research shows increased classifier accuracy after using negation handling.

3.1.2. Machine learning approach

The problem of negation scope detection in several studies is considered a classification task [17], [33], where each word is classified into the categories of negation scope and out of negation scope. In some studies, negation scope detection is also considered sequence labeling tasks [14], [34]. Several machine learning approaches can cover the weaknesses of rule-based approaches for negation scope detection in more complex sentences [15], [17], [33].

a. Traditional machine learning (TML): research [33] uses a support vector machine (SVM) to classify tokens that are or are not included in the negation scope. The system consists of two phases: cue detection and scope detection. The results show that the proposed method outperforms the baseline approach by around 20% for cue detection and around 13% for scope detection, judging from its F1-score. Other studies [34], [35] use conditional random fields (CRF). In their research, Councill *et al.* [35] produced a CRF model derived from the English dependency parser feature. This research limited negation detection to explicit negations in a sentence. The results of this study show increased accuracy for the lexicon-based sentiment analysis task. Enger *et al.* [34] uses SVM and CRF for negation cue and scope detection. The experiment results show increased performance results from the baseline approach. Their research aims to build Python-based tools for negation detection.
b. Deep learning (DL): a combination of approaches between convolutional neural networks (CNN) and Bi-LSTM for negation scope detection, was carried out by Lazib *et al.* [36]. The syntactic path-based hybrid neural network model is proposed to capture context based on sequence and syntactic information between candidate tokens and negation cues. This model aims to eliminate the need for hand-crafted features and improve the performance of previous approaches. The bi-directional long short-term memory (Bi-LSTM) model captures contextual information from each word in the sentence. On the other hand, the CNN model is used to extract additional information from the syntactic path between the negation cue and the candidate token. The feature output from both Bi-LSTM and CNN models is combined into a global feature vector, fed into a softmax layer, which classifies each token as inside or outside the negation scope. The model from the proposed approach produces a precision value of 78.31% and a partial correct scope (PCS) of 91.22%. The classifier performance shows an improvement of about 10% in PCS compared to some previous studies [37]–[39]. Other research carried out by Singh and Paul [14] using LSTM and Bi-LSTM was able to outperform the F1-score performance of the baseline approach [34], which used SVM and CRF for negation cue and negation scope detection. Based on these results, the LSTM model is better and provides flexibility to adjust parameters to build a model for handling negation with minimal human interaction for feature engineering. The BiLSTM model achieved the highest F1-score of 93.34%, outperforming the CRF and SVM models. Furthermore, [17] used the bidirectional encoder representation for transformers (BERT) approach to produce a NegBERT model. The performance of the NegBERT model can outperform all existing approaches for negation cue and

scope detection, making it a state-of-the-art model at this time. This result can be achieved because the approach used is BERT, which is based on a transformer architecture with an attention mechanism. This mechanism can learn contextual relationships between words in a sentence.

c. Reinforcement learning (RL), Lazib *et al.* [15] proposed a model for negation scope detection in text using reinforcement learning with labels at the document level. This model attempts to replicate human perception of document-level labels by training an agent to identify negation-affected words in documents. In this context, the agent learns by considering the correlation between sentiment and exogenous response variables such as rating values. This approach allows the model to handle the complexity of nested negations and contextual dependencies of words in a document. In some scenarios, it can even detect implicit negation cues in sentences. Another advantage is weak supervision, where identification of negation scope does not require word-level labeling for the training process but uses exogenous response variables as labels at the sentence level. The performance of the proposed approach is measured using Krippendorff's alpha coefficient. The results show a significant difference between manually annotated data and the output of the proposed approach. Another performance metric used for testing is the R^2 measure. The test results show that the R^2 performance of the proposed approach outperforms several rule-based approaches for negation scope detection.

3.1.3. Hybrid approach

Research conducted by Xia *et al.* [40] proposed a polarity shift detection, elimination, and ensemble (PSDEE) approach. PSDEE detects negation using a hybrid approach combining rule-based and statistical approaches. The FSW approach is used as a rule-based approach, and the weighted log-likelihood ratio (WLLR) approach is used as the statistical approach. A rule-based approach detects the scope of negation in sentences containing explicit negation cues. Next, WLLR is used to handle implicit contrast. Implicit contrast is a phrase in a sentence with a sentiment opposite to its label. Overall, the experimental results show that the performance of PSDEE for sentiment analysis is higher than several other approaches, such as Bag of Word without negation handling and models from research [19]. Other researchers [41] tried to implement the PSDEE approach; the experimental results from this study showed good accuracy but were very different from the precision and recall results; for example, the accuracy of the SVM classifier obtained was 90%, while the average precision was only 52%. This result is impossible because the average precision value will always be close to the accuracy value. This method is classified as a rule-based approach because it uses the WLLR, a statistical method that distinguishes it from machine learning approaches.

3.1.4. Summary of negation scope detection approach

The rule-based and machine learning approaches have their respective advantages and disadvantages. Table 1 shows the comparison of rule-based and machine learning approach for NSD. Although in terms of performance and flexibility, the machine learning approach can outperform rule-based approaches, in other aspects, such as dependence on labeled data, development time, and the need for experts, rule-based approaches can still outperform machine learning approaches.

Table 1. Comparison of rule-based and machine learning approach for NSD

Criteria	Rule-based approach	Machine learning approach
Dependency on data	It does not depend on labeled data; labeled data is only needed for the evaluation process, and it is possible not to use labels at all if it is not the main task.	Heavily relies on labeled data for the training and evaluation process.
Flexibility	It is static because decisions are based on predefined rules which are fixed in nature.	Dynamic in nature, able to adapt to new domains through training.
Basis of decision making	Pattern based on rules that have been defined.	Pattern based on learning results from the training process.
Development time	Faster development, no training process required.	Development takes longer because the data training process takes time, depending on the computational complexity of the machine learning algorithm.
Human expertise	Linguistic theory is needed to define the rules, which can be obtained from book references.	Linguistic expertise is needed for the dataset annotation process, so it needs someone who is an expert in linguistics as a data annotator.
Performance	Performance is quite good on simple sentences.	This approach can handle negation in more complex sentences and provides state-of-the-art performance for negation scope detection problems.

Table 2 describes the approaches commonly used for negation scope detection tasks based on previously discussed references. The rule-based approach is the most widely used and is quite old.

Meanwhile, machine learning approaches are currently dominated by deep learning approaches. The rule-based approach is still widely used to handle negation in SA, considering that NH is only a sub-task or auxiliary task for the main SA task. Even though deep learning for NH has high performance in terms of accuracy and F1-score, this approach has very high computational complexity [14] when compared to rule-based approaches.

Table 2. An overview of negation scope detection

Reference	TML		Deep learning				RL	Rule-based						
	SVM	CRF	LSTM	Bi-LSTM	CNN	BERT		RoS	FSW	NNA	FWL	TP	NS	FSW+ WLLR
[12]				√										
[14]			√	√										
[15]							√							
[17]						√								
[18]													√	
[19]								√						
[20]								√						
[21]								√	√	√	√			
[22]								√	√					
[23]											√			
[24]								√		√				
[26]												√		
[27]												√		
[30]											√			
[31]											√			
[33]	√													
[34]		√												
[35]		√												
[36]				√	√									
[40]														√
[41]														√
[42]												√		
[43]									√					
[44]									√					
[45]											√			

3.2. Literature survey of approaches for incorporating negation information into sentiment model

Approaches that use negation information to improve the performance of sentiment analysis are divided into four categories [12]. This process is carried out after the negation scope detection process [16]. In general, there are several approaches to negation handling, as shown in Figure 4.

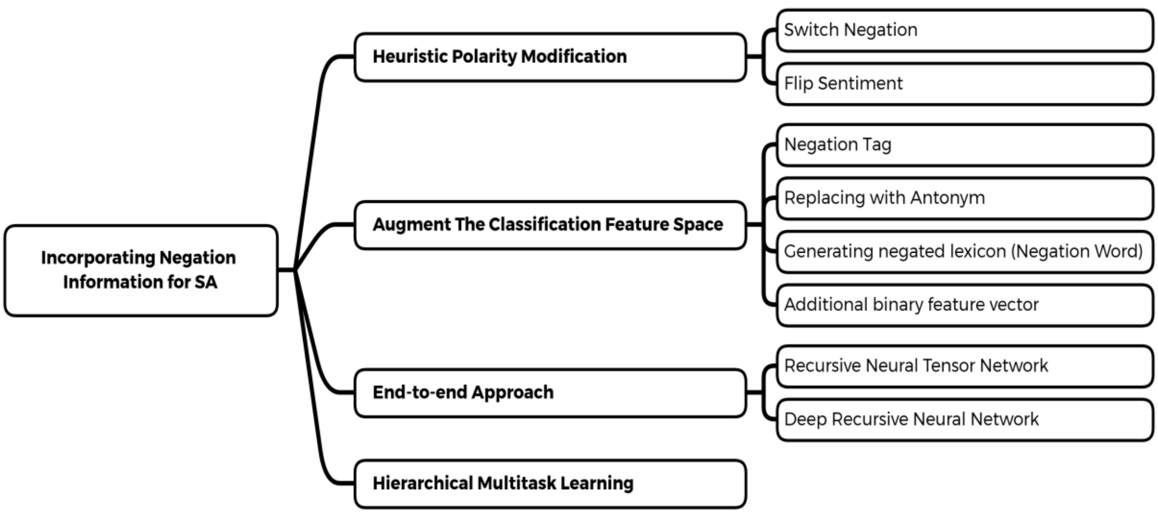

Figure 4. Approaches for incorporating negation into SA

3.2.1. Heuristic polarity modification (HPM) approach

In lexicon-based sentiment analysis, researchers initially employed basic heuristics like reversing or adjusting the polarity signal of a negated word to model negation. Below are several approaches that use heuristic polarity modification to incorporate negation into the sentiment lexicon.

a) Switch negation (SN): in research conducted by [26], [46], negation handling was carried out by reversing the sentiment score value. In this research, the negation scope is set heuristically by finding the negation cue and assuming that all the words between the negation cue and the following punctuation mark are the negation scope. This determination of the negation scope refers to research [19]. Another study [18] also carried out negation handling using the switch negation (SN) approach and modified the sentiment score to a broader scale (-5 to +5), not just on a value scale of 1 and -1.
b) Flip sentiment (FS): in another study, Bos and Frasincar [30] proposed an approach that considers negated words to have a sentiment orientation opposite to their sentiment label. Thus, words are negated in sentences with positive sentiment classes as negative words and vice versa. However, the performance of this approach still needs improvement compared to another proposed approach from this study named negated word (NW).

3.2.2. Feature space augmentation (FSA)

Negation handling in sentiment analysis based on a machine learning approach by adding a negation tag (NT) to the negated words was first carried out by [19], [20], and it produced a quite good classifier performance. Determining the negation scope includes all words after the negation cue until punctuation marks are found. Other research using NT, carried out by [43], [44], obtained increased classifier accuracy results after using NT. Other research [24] also uses this approach for negation handling, but for the negation scope detection approach, it uses the NNA approach. Experimental results show that the NT+NNA approach provides better results than the NT+RoS approach. However, research [12], stated that NT would add data sparsity and sometimes produce different performances because the model cannot explicitly connect the original and negated features.

Bos and Frasincar [30] used a feature augmentation approach for negation handling to build a sentiment lexicon. The researcher proposed approaches for negation handling, one of them named negated word (NW). The NW approach creates two entries for a word in the sentiment lexicon, one for the original word and one for the negated version. The NW approach provides better results than other approaches based on the test results. Thakkar *et al.* [45] carried out negation handling in sentiment analysis using antonyms, but words with negation usually have more than one antonym. Antonyms will be chosen randomly in this study, and the sentence context is not considered. The research results show an F1-Score value of 86.69%.

Other research on negation handling was carried out by Singh and Paul [14], and the negation information resulting from negation scope detection was used as an additional binary feature vector (ABFV) in the feature space. This research uses several methods for the sentiment classification process. The best performance was produced by Bi-LSTM, with an F1-score of 93.09%.

3.2.3. End-to-end approach

This approach does not require negation annotation on each word to capture the effect of negation in sentences. Negation information in sentences is formed in the classification model resulting from the training process. In research [42], a recursive neural tensor network (RNTN) approach was proposed; an RNTN model was trained to learn word representation and sentiment composition simultaneously, including negation information, which allows it to handle the entire sentiment analysis task from start to finish without requiring additional processing. RNTN is a recursive neural network (RNN) type that combines tensor-based composition functions. RNN works by processing input in structured data, not sequential data. The Stanford sentiment treebank (SST) dataset was introduced in this research. SST is the first corpus with labeled parse trees that allows a complete analysis of the effects of sentiment composition in language. The results of the experiments carried out in the study show that the RNTN model is very effective in handling negation in sentiment analysis tasks. The RNTN model has the highest accuracy for positive sentences and their negations, which shows its ability to learn the negation structure in positive and negative sentences. The superior performance of RNTN models is not just because they have more parameters than other approaches but because of their ability to effectively learn and handle sentiment composition. The accuracy results from RNTN can outperform the performance of several classifiers such as naïve Bayes, SVM, recurrent neural network (RNN), and matrix-vector RNN.

Irsoy and Cardie [47] proposed a deep recursive neural network (DRNN) approach. This study also used the SST dataset from previous research [42]. The resulting model can also capture negation information in the text well. The results of this research were able to outperform the RNTN approach from previous research [42]. Even though this approach performs well, it depends on a structured dataset.

Zhu *et al.* [48] proposed a prior sentiment-enriched tensor network (PSTN) approach. PSTN works by incorporating the prior sentiment of arguments into the sentiment analysis process. It considers the sentiment information of arguments and bridges the gap between models that use either the argument's sentiment or the negator's. The PSTN model has been shown to reduce fitting errors and outperform the recursive neural tensor network RNTN model, especially at greater depths where syntax and semantics are complex.

3.2.4. Hierarchical multi-task learning (MTL)

Barnes *et al.* [12] uses a cascading architecture consisting of lower and upper layers; the lower layer is for negation cue and scope detection, while the upper layer is for sentiment polarity prediction. The multi-task learning setup in this research means that the shared lower layer will receive supervision signals from both tasks, namely sentiment and negation. Bi-LSTM is used for feature extraction from the embedding layer while predicting negation cue and scope using linear-chain CRF with Viterbi decoding. Linear-chain CRF is used because it performs better for sequence modeling tasks, where this research considers negation cue and scope detection to be sequence labeling tasks. Sentiment polarity prediction is carried out on the second Bi-LSTM layer. The input received in the form of original embeddings is combined with the prediction results from the linear-chain CRF to produce a contextualized representation.

Furthermore, experimental results for negation cue and scope detection show better accuracy than several models, such as single task learning (STL) and the HEUR model. Sentiment classification experiments for the multi-task learning (MTL) approach produce better accuracy than STL, HEUR model, bag of words, CNN, Bi-LSTM, and self-attention networks+relative proportional representation. However, it is not as good as the Tree-LSTM and BERT models. One of the datasets used in this research is the SST dataset, the same as previous research by Thakkar *et al.* [45] that proposed the DRNN approach. The DRNN outperforms this hierarchical MTL regarding accuracy performance, but the difference in accuracy values is insignificant.

3.2.5. Summary of approaches for incorporating negation information into sentiment model

The approach used by several references discussed previously can be seen in Table 3. Based on the data in Table 3, the approaches often used are the heuristic polarity modification (HPM) approach, SN, and feature space augmentation, especially the NT approach. The performance of HPM for handling negation in sentiment analysis is quite good. However, the end-to-end and hierarchical MTL approaches are still superior when dealing with text with a more complex structure.

Table 3. An overview of approaches for incorporating negation information into SA

Reference	HPM		Feature space augmentation				End to End	Hierarchical MTL
	SN	FS	Neg. Tag	Antonym	NW	ABFV		
[12]								√
[14]						√		
[15]	√							
[18]	√							
[19]			√					
[20]			√					
[22]			√					
[24]			√					
[26]	√							
[27]	√							
[30]		√			√			
[31]	√							
[33]	√							
[35]	√							
[40]				√				
[41]			√					
[42]							√	
[43]			√					
[44]			√					
[45]				√				
[46]	√							
[47]							√	
[48]							√	

3.3. Negation handling in Indonesian sentiment analysis tasks

Several studies on sentiment analysis or text classification in the Indonesian language do not use negation handling [2], [3], [49]–[51]. On average, these studies only focus on word representation and the sentiment classification methods used. Research related to Indonesian sentiment analysis focusing on negation has been carried out by research [43] and [44]. Both studies use a rule-based approach defined by Indonesian syntactic rules. These syntactic rules were obtained from a dissertation published as a book [52]. In research [43], the performance of sentiment analysis increased when compared to the simple bag-of-words approach without negation. Research conducted in [44] tried to modify the rules from research [43] and added rules for double negation. This research shows an increase in sentiment classification performance compared to previous research. However, research [43] and [44] has several limitations, such as being unable to resolve negation if the positions of the negation cue and negation scope are not close because the negation scope uses the FSW approach. Another limitation is that it does not use the syntactic rules from [52] as a whole; the rules defined are only limited to basic sentence types or what are called core single sentences [52], and there are no negation provisions for other types of negation such as the type of negation in special constructions. The approach to negation scope detection for Indonesians is still limited to a rule-based approach. This limitation is due to the unavailability of an Indonesian language dataset with annotations for the negation scope detection task.

4. RESULTS AND DISCUSSION

This study investigated various approaches for negation handling in sentiment analysis. Negation handling consists of two tasks: NSD and incorporating negation information into the sentiment model. It was found that the NegBERT model has been shown to outperform all existing approaches for NSD tasks, making it a state-of-the-art performance in this field. Furthermore, the approach for incorporating negation information into the sentiment model, the end-to-end approach, and the MTL approach show effective results, indicating the potential for more advanced techniques to enhance sentiment analysis tasks. Despite these advancements, notable research gaps exist in addressing implicit negation cues and the absence of approaches combining rule-based and machine learning for NSD.

Our study reveals that the NegBERT can achieve a good result because the approach is based on a transformer architecture with an attention mechanism. This mechanism can learn contextual relationships between words in a sentence. Meanwhile, end-to-end approaches such as RNTN and DRNN excel in capturing negation information within text data. These models demonstrate the ability to handle complex sentiment compositions, including negation structures, leading to enhanced sentiment classification accuracy.

NegBERT for NSD has high performance in terms of accuracy and F1-score. However, this approach has very high computational complexity compared to rule-based approaches. As previously explained, negation handling is a sub-task. Logically, when the sub-task and main task work together using machine learning, then computational complexity will increase. On the other hand, the end-to-end approach performs well; studies on the end-to-end approach are still minimal due to data requirements. Although MTL is not as good as an end-to-end approach in terms of accuracy, the dataset availability for the MTL approach is more accessible than the end-to-end approach, which requires structured data. Another limitation based on previous research is the absence of labeled datasets for NSD tasks in the Indonesian language. This limitation has restricted the exploration of machine learning approaches for NSD in Indonesian sentiment analysis, which primarily relies on rule-based methods.

Furthermore, some studies have attempted to tackle implicit negation issues using reinforcement learning and a combination of rule-based and statistical approaches. However, the exploration of implicit negation cues remains relatively scarce. Another research gap is that no approach combines rule-based and machine learning for NSD. The combination of these two approaches has the potential to get better results because it can cover the weaknesses of rule-based, which has static rules, and the weaknesses of machine learning, which requires significant computing resources, like in the NegBERT model.

The implications for future research underscore the potential for hybrid approaches that combine rule-based and machine learning methods to address complex negation scope detection challenges in sentiment analysis. By leveraging the strengths of both approaches, researchers can achieve better results in handling negation structures in text data. While significant progress has been made in negation handling for sentiment analysis, research gaps still need to be addressed. Future research should develop comprehensive strategies for handling explicit and implicit negation cues in sentiment analysis. Based on the previously discussed references, it is important to explore hybrid approaches, such as combining rule-based and machine-learning methods, to enhance the accuracy and efficiency of sentiment analysis tasks, which may lead to the solution of the implicit negation problem and solution for Indonesian sentiment analysis task, where labeled datasets are limited.

5. CONCLUSION

In conclusion, this literature review explored the handling of negation in sentiment analysis. Significant research gaps are identified as limited focus on implicit negation cues and the absence of a combined rule-based and machine learning approach for NSD. While some studies have explored these issues, research on implicit negation cues and the combination of rule-based and machine learning for NSD remains scarce.

Based on the previously discussed references, the most widely used approach is the rule-based approach. However, the NegBERT model emerges as a state-of-the-art performer in NSD tasks, outperforming existing approaches, although the computational complexity of NegBERT poses a challenge, especially compared to rule-based approaches. For incorporating negation information into the sentiment model, the end-to-end and MTL approaches also demonstrate effective results, showcasing the potential of advanced techniques in enhancing sentiment analysis tasks. While performing well, the end-to-end approach faces limitations due to data requirements. MTL, though more accessible in terms of dataset availability, falls short in accuracy compared to the end-to-end approach.

Future research should address these gaps by exploring hybrid approaches that combine rule-based and machine learning methods. This gap is crucial for overcoming challenges in explicit and implicit negation cues. Apart from that, the NSD task for the Indonesian Language needs to be improved because there is no labeled dataset. Developing comprehensive strategies for handling negation structures in sentiment analysis tasks will improve accuracy and efficiency in this evolving field.

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