Capturing Negation scope using Base Phrase Chunk in Arabic Sentiment Classification

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Abstract
One of the sentiment analysis challenges in the Arabic language is the exploration of the effect of negation. Most of the previous works in Arabic sentiment analysis neither include the negation concept in sentiment analysis nor clarify the negation words list that they rely on. This paper shows the ongoing work to add negation to Arabic sentiment analysis. Different types of methods to deal with the negation in the sentiment analysis in Arabic are proposed. Our proposed method that relies on the shallow parse tree achieves the best result in dealing with negation. In addition, the experiments and evaluations that were conducted in this work show that including the negation in the sentiment analysis for Arabic improves the performance of the classifier.

Keywords:
Sentiment Classification, Negation scope, Arabic Natural Language Processing, Arabic Sentiment Sentence Classification, Machine Learning.

1. Introduction

The extraction of sentiment from a text has attracted a considerable amount of attention over the past decade, both in industry and academia. Sentiment analysis attempts to extract the emotions and opinions of individuals from their writing about specific entities. Much of the research has been undertaken in English, as this is the dominant language of science. Arabic natural language processing has therefore become attractive to researchers, due to its complexity and the scarcity of available resources. According to Farghaly and Shaalan [1], the field of Natural Language Processing (NLP) in Arabic is still at an early stage of evolution, despite the efforts being made with the fundamental NLP tools of Arabic.

Sentiment Analysis (SA) of Arabic is also still in its early stages, and increased effort and reliability of low level tools are required in order to build upon this foundation. The most common linguistic aspect that affects sentiment analysis is negation. Negation often changes the sentiment and polarity of a sentence. For example, the following two sentences “this is a good movie” and “this is not a good movie” will have the same polarity if the negation item “not” is ignored in the sentiment analysis. The positive sentiment associated with the word “good” is inverted into negative sentiment for the phrase “not good” and may not necessarily be as negative as the sentiment associated with the word “bad”. Therefore, negation items and their scope in the sentence have to be taken into account during sentiment analysis [2]. Determining negation in sentences is not an easy task because of the complexity of the nature of negation. In the Arabic language, the negation words such as “not” and “no” not only show negation in the sentence but other semantic meanings. In addition, the negation could use sometimes to express other meanings or styles such as in questioning and wondering sentences.

2. Related Works

Elhawary and Elfeky [3] considered the negation concept in their work. They relied on the Arabic lexicon to calculate the sentiment orientation score of each word or phrase. While the counting process is running, the negated word of the phrase is flipped. Farra et al. [4] also take care of the negation while attempting to capture the sentiment of the Arabic text. The negation issue is considered in this work by only counting the frequency of the negation words in the sentence while they attempt to build a semantic feature of the sentence depending on the Arabic sentiment lexicon. The feature used was the frequency of each positive, negative, neutral word, special character and the frequency of the negation words. Hamouda and El-taher [5] attempted to build a sentiment analyzer for comments on Arabic Facebook news pages. They compared different machine learning algorithms with different features. One of these was dealing with negation in Arabic. They counted only five different negation words, whereas there are more than these, even without counting negation words in the dialects. They only add the percentage of negation words in either the post or the comment as the feature, without considering the effect of the negation on the word or phrase. They claimed that adding negation words features besides the features of all words in posts and comments gives the best performance.

There are some issues here in the previous work. Firstly, the works did not mention the Arabic negation words used, stating only that they used around twenty words as

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negation words. Secondly, there is the issue of how they determined the negated words or phrase that come with the negation word in the sentence. This might affect the process of the sentiment analysis since it has the possibility of changing the polarity (i.e. its polarity type and strength). In addition, relying on a simple representation (i.e. frequency counts of negation words or polarity words) would not capture all the semantics and syntax of the sentence in order to assist in sentiment classification. Some of the proposed methods may work only for the domain chosen, such as the posts and the comments on Arabic Facebook news pages [5]. This might, or might not, work with normal Arabic sentiment analysis.

3. Negation in Arabic

Negation in the Arabic language is used to negate the idea of the sentence. There are two styles of negation [6, 7]. The first style uses negation terms, which is explicit negation. The second style is implicit negation which does not use negation terms or words, instead, some of the words in a sentence carry a negation meaning. In this research project, we focus solely on one type of negation which is explicit negation, and the ways in which this influences the Arabic sentiment analysis.

Table 1: Negation List Words in Arabic

Arabic Negator	Transliteration and English meaning	Language Type	Its Type
لا	*lA*- Not or No	CA/MSA/DA	
لم	*lm* - Not	CA/MSA/DA	
لما	*lmA*- Not	CA/MSA	
ما	*mA* - Not	CA/MSA/DA	Preposition
لن	*ln* - Not	CA/MSA/DA	
إن	*In* - Not	CA/MSA	
لات	*lAt* - Not	CA	
مو	*mo*- Not /No	DA	
لات	*mish*- Not / No	DA	
غير	γ*yra* - But	CA/MSA/DA	Noun
ليس	*lysa* - Not	CA/MSA	Verb

Explicit negation is a negation style that is used to negate the sentence using one of the negation words. The negation terms, tools, items, or words in Modern Standard Arabic (MSA) [6] or Dialect Arabic are shown in Table 1. Some of them also could be used with a nominal sentence, or with a verbal sentence, in order to negate the sentence. The majority of these negation words are used mainly in Classical Arabic (CA), Modern Standard Arabic (MSA), as well as in Dialect Arabic (DA) [1]. DA has specific negation items that are used for a specific dialect. For instance, the negation word (mw / No or Not)[1] is used in a number of specific dialects in order to express the same meaning as using ‘lA ’ meaning ‘not’ or ‘no’).

A number of negation terms are used not only for negation; they may also be used in other styles and semantic meanings in Arabic. The negation word (mA/ What) may be used in various ways, such as in condition, interrogative, and wondering. For example, Figure 1 displays an example of an Arabic sentence that use negation items but is not for negation purpose. In this sentence (mA / What) is used to express the question, rather than to negate the sentence

4. Motivation

Dealing with negation in natural language applications such as sentiment analysis plays a key role when it inverts the sentiment orientation of the sentence. Moreover, the negation and its effects in the domain of Arabic sentiment analysis have not been studied a lot compared to other languages such as English [2, 9, 10]. A little Arabic sentiment analysis work considers a negation during the process of classification [3, 4, 5]. However, most of them do not explain the process of how they deal with the negation or even mention the negation words that they used. Therefore, this paper aims to fulfill these contributions:

a) Focus on the negation in the Arabic language: describing how negation is used in the Arabic language and showing its words.
b) Showing the importance of negation in the Arabic language by studying the existence of negation in Arabic sentiment corpus and the percentage of the negated sentence in the wrong class after the classification process.
c) Proposing a new method to deal with negation for the classification of Arabic sentiment using machine learning algorithms and providing results of experiments to compare it with traditional approaches.

5. Importance of Negation in Sentiment of Arabic Text

This section illustrates the importance of using negation within the sentiment in Arabic text. This importance may be expressed by showing the percentage of the opinioned sentences that have negation words.

[1] Throughout this paper, Arabic words are represented in either (transliteration scheme [8]/ English translation) or (Arabic word/transliteration scheme / English translation)

5.1 Arabic Sentiment Corpus

The author of this work builds their own corpus due to the scarcity of sentiment Arabic corpus. The research corpus was built from five different genres, which include news, reviews of the news, user market reviews, restaurants reviews, and movie reviews. The news data has been taken from the Sabq[2] website among different domains which are local, sport, economics, technology, and social news. The reviews of the news have also been taken from the same website where individuals can add their comments and feeling about the news. The Souq[3] (considered the Amazon marketplace for Arab countries) is used as a source for market reviews. The last two data sets have been taken from previous works. The restaurant reviews have been taken from the work of [11] which captures the review of the user concerning restaurants[4]. The movie reviews were taken from the movie review website[5] and are used in [4]. Table 2 shows the information about each data set.

Table 2: Basic Statistics Concerning the Corpus

	Movie Rev.	Restaurant Rev.	Market Rev.	News Com.	Newswire
Num. of document	101	1,943	2,016	1,925	283
Num. of sentences	5,290	10,175	2,507	9,919	5,979
Positive sentence	1649	2953	964	1649	459
Negative sentence	3008	2051	772	3008	363
Neutral sentence	1263	396	382	1263	47
Subjective sentence	1547	5400	2118	5920	869
Objective sentence	3743	4775	389	3999	5110

keys: "Num" for number, "Rev" for reviews and "Com" for comments.

Two Arabic educated individuals have been chosen to annotate the data. Each annotator was given guidelines. First, they should determine if the document is subjective or objective. Second, they need to establish the polarity of the subjective text among three categories, these being positive, neutral, and negative. Third, the annotator should go over each sentence in the document, noting its polarity if the sentence is a subjective one, otherwise, the sentence should be seen as objective. The first step was to train the two annotators, who were then asked to work on the same data set which contained around 33% of the sentences. During this process, the inter-annotator agreement between them was calculated using the Kappa coefficient [12] which was between 0.72 and 0.84. In order to get this data set, contact the first author.

(ماهذا الذي تقوله ؟ / *mA hðA Alðy tqwlh?* / what are you saying?)

Fig. 1 Example of Using Negation in Different Contexts

5.2 Percentage of the Negation in the Corpus

In order to compute the percentage of using negation in each data set of the corpus, it is necessary to specify the negation words listed first, then the method in which the negated sentence should be determined. Depending on the investigation into the Arabic grammar rule concerning negation words, there are around 19 negation words in MSA, including all morphological terms of (lysa / Not). We add two more negation items that relate to and are used in DA which is (mo and mish), Figure 1.

The typical method of writing these negation words in Arabic is by adding a space before and after it. For purposes of simplicity, the typical method will be considered while the negation is counted in the sentence, as well as any sentence that has a negation word is counted as a negated sentence. We follow this procedure, due to the fact that there is no annotated negation corpus for Arabic available.

Table 3: Percentage of Negated Sentence in Each Class of Subjectivity

Data-set	Objective	Subjective
Movie	**48.7%**	31.3%
Restaurant	32.8%	**57.2%**
E-Market	6.7%	**83.3%**
News comments	25.1%	**64.9%**
News	**56.1%**	23.9%

Table 3 depicts the percentage of sentences that contain any of the negation words for each data set in each class which is either objective or subjective. For all objective or subjective sentences, the sentence in this class is counted if it has a negation word. Negation words tend to be used more in a subjective class sentence in order to negate the sentiment orientation of the sentence in the three data sets. In the news data set, it appears that the negation is used frequently in the case of objective sentences, due to the fact that the majority of sentences in this domain may carry factual information. Therefore, the negation words here are used most to negate factual information rather than reverse the sentiment orientation of the sentence.

Table 4: Percentage of Negated Sentence in Each Class of Polarity

Dataset	Positive	Negative	Neutral
Movie	10.3%	**11.2%**	9.8%
Restaurant	19.3%	**30.8%**	7.1%
E-Market	26.2%	**39.9%**	17.3%
News comments	16.9%	**34.6%**	13.4%
Newswire	8.7%	**12.9%**	2.2%

The same study is undertaken for the polarity classes. Table 4 shows the percentage of the sentences that contain negation words in each class for each data set. The bold text in this table highlights the highest percentage among

[2] https://saudi.souq.com /

[3] https://sabq.org/

[4] https://www.qaym.com/

[5] https://www.filfan.com/

the three classes. It appears that negation is frequently used in the case of the negative class in order to negate the positive polarity to a negative one. In addition, the negation words tend to be used more in the case of the positive or negative polarity classes, when compared to the neutral one

5.3 Percentage of the Negation in the Sentiment Classification

The final investigation that has been undertaken on the corpus is displayed in Table 5. This attempts to establish the percentage of the negation that has occurred after the classification process on the sentence level. In this investigation, the classification process for all datasets and for each of the categories "subjectivity or polarity" are performed based on a support vector machine classifier (SVM - linear kernel) with uni-gram features. The number of negated sentences that are incorrectly or correctly classified are then counted. For example, there are around 108 negated sentences with 32.3% in the error classification, whereas there are 162 negated sentences with 22.3% in the correct part in the subjectivity classification for the Movie reviews data set. This implies that there are more negated sentences that are incorrectly classified and correctly classified, and the classifier needs to be aware of negated sentences during the classification process in order to avoid this issue. By looking at Table 5, we found that there is a higher percentage of negated sentences that are incorrectly classified than correctly classified in different classification categories among all datasets. This may demonstrate the importance of the negation words and their effect on other words or phrases. Therefore, the sentiment analysis should address this issue during the classification process.

Table 5: Percentage of The Negation That Has Occurred After the Sentiment Analysis Process

	Subjectivity		Polarity 1		Polarity 2	
Data-set	Error	Correct	Error	Correct	Error	Correct
Movie	**32.3%**	22.3%	**48.8%**	22.8%	**45.9%**	29.5%
Restaurant	**30.0%**	19.5%	**24.9%**	18.4%	**26.1%**	19.1%
E-Market	24.1%	**30.6%**	**34.5%**	30.0%	**43.6%**	28.8%
News Com.	20.9%	**25.1%**	**31.0%**	29.1%	**29.6%**	29.5%
Newswire	**20.3%**	9.4%	**18.9%**	18.0%	16.0%	**17.6%**

keys:
"Polarity 1" when there are two classes positive and negative.
"Polarity 2" when there are three classes which are positive, negative and neutral.
"Com" refers to comments on news

6. Approaches to Deal with Negation

This paper suggests that the work should be carried out in two areas in order to employ negation in Arabic sentiment analysis. The first area depends on a simple method of discovering negation. For the second area, more complex models will be relied upon in order to establish how to discover negation in Arabic sentences before the sentences are processed for sentiment analysis.

6.1 Primary Method

First of all, the bag-of-words without stop and negation words are used as a baseline to compare different approaches. The First method is the one that is built with the BOW and considers negation items. This model would be captured the negation item during the building of the feature model space. It also shows whether the particular text has negation or not.

Adding the negation tag "NOT" to a word if a given sentence contains one of the negation items is another proposed method. This would capture the effect of the negation on the following words. Taking the negation word alone in the space feature model is not enough to capture the actual impact of the negation on the text. Therefore, we have to find the best scope or effect of negation in the text. Capturing negated words can be achieved using various mechanisms. Different windows would be compared regarding negated tags. This would be the other method in our work. The widows will be varied from one to three words after the negation item. The effect of the negation on the sentence will be captured because the negation sometimes affects the word after the negation word or other far word. The longer effect of negation will be added to the sentence by proposing that the negation item may negate all the words in the sentence. This approach will tag all words after the negation words with the "NOT" tag until the first punctuation appears.

6.2 Base phrase chunking Method

Base phrase chunking (BPC) reveals the phrase that the words belong to. In natural language processing, BPC is a process that separates and segments a sentence into its phrases such as nouns, verbs, or prepositional phrases. This represents a shallow parser tree of the sentence. This will be depended upon in order to determine the scope of the negation by assuming that all words in the same phrase as the negation word are negated. The use of BPC will be used to direct the work in order to determine the negation and its effect on the sentences. In the next following discussion, I will use an English example in order to make the idea clear. Let us consider this sentence "All my classmates have not been like the horrible movie except me" as an example. The BPC for this sentence would be as: "(NP All (NP my classmates)) (VP have not (VP been like (NP the horrible movie))) (PP except NP me)". We notice that the negation item "not" belongs to the verb phrase “VP”. Our method supposes that all the words in the same phrase chunk should be negated by the negation item. Therefore, the following words (like horrible, movie) should be in the scope of the “Not” item. The result would be negated the liking of the horror movie. All of these phrases would be used in the feature model space.

7. Experimental Setup

This section have two parts. The first part describes the data that have been used. The second part illustrates the process that has been performed to test out proposed methods.

7.1 Dataset

We use the same data sets that we built in order to investigate the importance of the negation in the Arabic Sentiment that is explained in section 5.

7.2 Classification Process

The pre-processing phase contains four steps before the documents or sentences pass to the classifier. The first step includes filtering out all rubbish data that might be found in the text, including single letters or non-Arabic characters. The second step is to normalize long words that may make some letters redundant. For example, some users tend to write Arabic words with some repeating letters such as in Figure2. The normalization here will reduce the repeated letter to one letter only as it is shown in Figure 2. The third step is to use the AMIRA [13] toolkit for all data, in order to prepare the BPC tag of the text. The final step involves removing the stop words lists and modifying, them to deal with this while it builds the vector space model that represents the words. Stop word lists in [14] were used.

Befor the normalization process
(مشكووووووور / *mškwwwwwwwr* / Thanksssss)
After the normalization process
(مشكوور / *mškwr* / Thanks)

Fig. 2 Example of Letter Repeating

To evaluate the negation awareness in sentiment analysis, many experiments were undertaken using a support vector machine classifier (SVM) with a linear kernel. As a basic step, the uni-gram model is applied to the learning and testing process. we relied on the scikit-learn library [15] for using machine_learning classifiers. Due to the space and time limitation, the process of classification is performed on the subjectivity and binary polarity when there are only two polarity classes (positive and negative). It is also carried out on sentence-level classification.

For experiments that test proposed techniques in this project follow these steps:

1. *Whenever a negation item is found in a sentence, the sentence is considered negated with that item. This is not applicable in regard to the intelligent approach.*
2. *To build feature vectors used by classifiers, a uni-gram model is used that takes the distinct words within the data set to build feature vectors in regard to each sentence.*
3. *The artifact “NOT” tag was added to all negated words after the negation item in negated sentences. If the word x is preceded by the negation words, then the new feature word will be added to the model, which is x NOT. This method follows the one undertaken in the English language by [16].*
4. *The proposed approaches differ based on which word should have the “NOT” tag in the feature vector.*
5. *5-fold cross-validation is performed to test proposed methods*

In order to measure the performance of the classifier, the F1 score is used after computing the precision and recall. After the F1 score is computed individually for each class, the weighted average for F1 is calculated in order to establish a single value that can be used to evaluate the performance of the classifier. For example, the classifier is used to classify subjectivity, i.e., the document is either subjective or objective. The F1 score will be calculated for each class individually (F1 for the subjective and F1 for the objective). Finally, a weighted average of F1 is calculated, resulting in a single value. The F1 and the weighted average F1 are calculated as:

$$F1 = 2\,\frac{Precision\,.\,Recall}{Precision + Recall} \tag{1}$$

$$F1_{weighted\ Avg.} = \frac{\sum_{i=1}^{n} w_i\, f_i}{\sum_{i=1}^{n} w_i} \tag{2}$$

where f is the F1 score for each class, and w is the number of documents or sentences that are used in test classification experiments

8. Result and Discussion

The following section discusses the experiments performed and the results obtained in order to provide an evaluation of the effect of negation in Arabic sentiment analysis by comparing different approaches related to the concept. All the experiments are classified on the sentence level into three different types: subjectivity (contains two classes: subjective and objective), and polarity (contains two classes: positive and negative).

8.1 Experiments of Primary Techniques

The first experiment investigates the effect of adding negation words to the feature vector. Most of the research in regard to Arabic natural language processing considers negation words as a stop words list that should be removed before building the feature vector. This may work well with some NLP problems, but it does not work for sentiment analysis. Therefore, we compare two feature models: one that considers negation words as stop words and eliminates them from the feature vector "NoN: No Negation" and the other that includes negation words within the feature vector "WtN: With Negation". The uni-gram model is used to build the feature model. Table 6 illustrates the results of SVM using these models. The first column represents the first feature model, which is "NoN: No Negation". The second one shows the second model that includes negation words with the feature model and removes stop words "WtN: With Negation". The values display the average F1 score for the performing SVM within the specific feature model. By looking at this table 6 in both classification types, we notice that the results are better when the second model is used, which includes negation words with the feature model. It is clear that negation words play role in sentiment analysis because they flip the sentiment orientation of the sentence. Additionally, the performance of the classifier increases between 1 and 2 percent in most cases. In some cases, the difference between these models is as large as 8 percent, such as in the case of the two classes of polarity in the movie review dataset, table 6, with polarity classification. As a result, the model that uses negation words to build the feature model is considered a base model that can be used to compare other approaches in this field.

Table 6: Different Approaches of Injecting Negation in Arabic Sentiment Classification

	Subjectivity Classification							Polarity Classification						
Dataset	NoN	WtN	WD1	WD2	WD3	HS	BPC	NoN	WtN	W1	W2	W3	HS	BPC
News comments	65%	67%	68%	70%	70%	68%	**70%**	56%	56%	56%	**58%**	57%	57%	55%
Restaurant	67%	69%	70%	70%	70%	70%	**72%**	72%	73%	74%	75%	75%	75%	**84%**
E-Market	89%	**90%**	89%	89%	89%	895	89%	88%	**90%**	**90%**	**90%**	**90%**	**90%**	84%
Movie	40%	41%	42%	**43%**	**43%**	**43%**	**43%**	48%	56%	55%	57%	57%	57%	**81%**
Newswire	30%	31%	32%	**34%**	33%	32%	33%	78%	78%	78%	**79%**	**79%**	**79%**	78%

keys:
"NoN" without caring about negation items. "WtN" With negation items in the feature model.
"WD1" use NOT tag with one word. "WD2" use NOT tag with two words. "WD3" use NOT tag with three words.
"NC" counting the negation items. "BPC" use NOT tag on the words in the same phrase where the negation item is in.

The same tables illustrate and compare different window sizes in order to capture the effect of negation. As explained early in previous sections, the artifact "NOT" tag will be added to the negated word while the feature vector is built. The first window will include one word after the negation word in order to add "NOT" to the word. This situation refers to WD1, which is the third column. WD2 uses two words after the negation item, which is shown in the fourth column. The fifth column displays WD3, which includes three words after the negation item. The HS column shows the whole sentence window that includes all of the words after the negation item until the end of the sentence. Within the subjectivity classification, using these techniques increases the results by one percent in most cases, except in the case of the market review. The length of the sentence may be affected by these techniques, as shown by the market review having the shortest sentence length compared to other data sets. Another explanation may be in regard to the assumption that any sentence having negation words would be negated. This situation may not work well in this domain because some of the words used may be in a different style than negation. However, the best window size is when either 2 words or the whole sentence are used after the negation item in the data-set domains. Performance increases by 1 to 2 percent in comparison to the baseline. In the case of the polarity classification, the results are similar to the subjectivity classification. The best window size is when 2 words are used after the negation item in the data-set domains.

8.2 Experiments of BPC Technique

It seems that the BPC technique achieves good results in most cases. In the case of subjectivity, the performance of the classifier with the BPC feature model method is improved. The F1 score increases by 2 to 4 percent across some of the data sets. The most interesting results are those of the polarity classification, table 6. In the case of the long "Movie" and medium sentences "Restaurant", the result increases dramatically. For example, the result goes from 56% to 81% in the case of movie reviews. Additionally, it increases from 73% to 84% in restaurant reviews.

This may be due to using Base Phrase Chunk (BPC) to capture the scope of the negation in the sentences. This technique may work better in capturing the two types of polarity than in the subjectivity classification.

On the other hand, the results decrease by 6% in the case of market reviews. This may be due to the nature of the data set. The market reviews have the shortest sentence length compared to the other data sets. Additionally, more investigation should be done in order to find out other reasons why this technique does not work well in regard to market reviews.

9. Conclusion and Future Work

Our investigation shows that taking negation into account while analyzing sentiment for Arabic text may help and improve the performance of the classifier using a machine learning algorithm. This paper describes and comes up with a comprehensive list of negation words in the Arabic language and their uses. Besides that, the importance of the negation in Arabic text has been shown as well as the percentage of error in classification that has negation words. The results achieved by this paper demonstrate the potential gain that might be afforded obtained by including negation.

Different approaches are proposed and compared to find the best ones that work within Arabic sentiment analysis. primary approaches include adding negation with the uni-gram model, different window sizes to capture the scope of negation, counting negation items in a sentence, and using BPC with negation. The best approach is using BPC to capture the negation scope and to build feature vectors that train classifiers. Another good method to use is window size with two words after the negation item.

There are many different directions to take in this field in order to continue work on negation and Arabic text sentiment. One direction relates to the negation items. Instead of relying on all of the negation items, we can choose the most common negation items that are used in negation and compare them with the primary method. Working with implicit negation that reflects negation without using negation items could be one direction in future work. More work is needed to capture these styles and find out what words or meaning is negated in order to add that to the feature vector. The other possible work is to use the actual parse tree that shows the total structure of the sentence and displays the relationship between words. This tree would give better negation scope compared to the BPC. Whenever the negation is found in the tree, all descendant node should be within its scope. Lastly, future work may include work on the diminished and intense words that may boost or diminish the actual sentiment of the text.

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