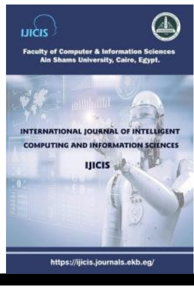
IJICIS, Vol.23, No.1, 29-40
DOI: 10.21608/ijicis.2023.176628.1232

International Journal of Intelligent Computing and Information Sciences

https://ijicis.journals.ekb.eg/



ARABIC NEGATION AND SPECULATION SCOPE DETECTION: A TRANSFORMER-BASED APPROACH

Ahmed Mahany
Computer Systems
Faculty of Computer and Information Sciences, Ain Shams University
Cairo, Egypt
ahmedmahany@cis.asu.edu.eg

Heba Khaled
Computer Systems
Faculty of Computer and Information Sciences, Ain Shams University
Cairo, Egypt
heba.khaled@cis.asu.edu.eg

Said Ghoniemy
Computer Systems
Faculty of Computer and Information Sciences, Ain Shams University
Cairo, Egypt
ghoniemy1@cis.asu.edu.eg

Received 2022-11-23; Revised 2023-01-01; Accepted 2023-02-25

Abstract*: Detecting the negation and speculation linguistic phenomena is vital for the performance of Arabic Natural Language Processing (ANLP) tasks. The negation and speculation scope detection problems have been addressed in a number of studies where most of them focused on the English and Spanish languages. This is due to the lack of corpora annotated for negation and speculation. In this work, the ArNeg corpus, annotated with negation, is extended by annotating it for the speculation to build the ArNegSpec corpus. In addition, we propose a transformer-based learning approach for detecting both the negation and speculation in Arabic texts. The AraBERT models with a Bidirectional Long Short-Term Memory and a Conditional Random Field (BiLSTM-CRF) as a sequence classification layer to achieve this goal. The results reached an F1 measure of 98% for cue identification for both negation and speculation. The proposed approach enhanced the evaluation results of the negation scope detection by 6% in terms of the F1 measure compared to the previous study. Furthermore, it achieved a 95% F1 measure for the speculation scope detection and a PCS value of 96% for both the negation and speculation scope. This approach shows the feasibility of transformer-based learning models in the sequence classification tasks as the detection of the negation and speculation in Arabic.*

Keywords: *Arabic Language, Negation, Speculation, ArNegSpec, AraBERT.*

1. Introduction

The growth of textual data across numerous domains, like social media data, product reviews, and biomedical data, has arisen the necessity to make use of all this available data. Arabic Natural Language Processing (ANLP) has attracted an extraordinary amount of attention, making it one of the most significant research areas in Arabic research and academic communities [1]. Furthermore, the United Nations recognizes Arabic as one of the six official languages. In the last decade, the research in ANLP

***Corresponding Author**: Ahmed Mahany

Computer Systems Department, Faculty of Computer and Information Science, Ain Shams University, Cairo, Egypt

Email address: ahmedmahany@cis.asu.edu.eg

started to increase, and it has been included in many competitions, such as in SemEval 2022 [2]. These competitions and events accelerated the ANLP's research pace, as in sentiment analysis and information retrieval tasks. Classical Arabic (CA), Modern Standard Arabic (MSA), and Dialectal Arabic (DA) are the three common forms of the Arabic language. The CA form is used for the Quraan and ancient literature, while the MSA is used in written official documents like newspapers and governmental documents. The DA, on the other hand, covers the modern forms of Arabic texts posted on social media and e-commerce platforms. The DA also differs based on the geographical regions of the Arab countries [3]. Nevertheless, the written text shares significant commonalities despite the differences in Arabic form [4].

The phenomenon of negation and speculation are widely utilized in language to convey information about the polarity and certainty of facts. Negation is defined as "the exact opposite of something; the act of causing something not to exist or to become its opposite" [5]. On the contrary, speculation is "the act of forming opinions about what has happened or what might happen without knowing all the facts" [6]. It indicates that there is no sufficient proof in the text that the information is 100% accurate. The negation and speculation scopes are detected by identifying the cues and their scopes. Cues are the words that confirm the existence of this phenomenon, and their scopes are the affected statements within texts [7]. The existence of negation cues in a phrase does not necessarily imply a negation instance in some cases; however, in rare cases, it may affirm the polarity of the subsequent sentence clause [8]. Contrary to this, in other cases, the negation cue may be coupled by a non-negating speculative text, understood from the context, and the speculation detection may be more complex [7].

The continuous growth of the data adds more challenges for text mining researchers as these data may feature negated or speculative content. These affected texts may lead to performance degradation of the NLP tasks: Sentiment Analysis (SA) [9], Machine Translation (MT) [10], and biomedical information retrieval [7]. For example, in the SA task, a negation cue can flip the classification output, and the degree of speculative content may affect the certainty of this output [11]. This proves that extracting or classifying text is challenging because texts frequently contain negating or speculative cues that lead to inaccurate identification output. Consequently, detecting negated and speculative statements in texts is important to enhance the performance of NLP tasks.

Negation detection has attracted considerable interest over the past decade; however, there are few available corpora for the Arabic language compared to English and Spanish [12]. Also, there are fewer corpora for speculation than for negation, with the bulk concentrating on medical data [13]. Meanwhile, both are language-dependent linguistic features that must be studied in all natural languages, including Arabic. Therefore, annotating an Arabic corpus with negation and speculation is necessary to enhance the performance of ANLP tasks as in the studies of the other languages [13], [14]. These studies tackled the negation and speculation problems using simple rules [15] or advanced deep learning approaches [9]. In this paper, the corpus built in this work [16] is extended by annotating the corpus for speculation. Moreover, a transformer-based approach is proposed to detect the negation and speculation scopes in Arabic texts. It includes a Bidirectional Encoder Representation Transformer (BERT) model and a classifier of Bidirectional Long-Short Term Memory and Conditional Random Field (BiLSTM-CRF) layers. The contribution of this paper is:

- A manually annotated corpus, **ArNegSpec**, of 3,000 sentences with negation and speculation.
- Proposed a BERT-based BiLSTM-CRF approach for detecting the negation and speculation scope in Arabic.

- Outperform the results of the negation scope detection model of the previous work.

The rest of the paper is organized as follows: Section 2 demonstrates the related work that highlights the several techniques used in detecting the negation and speculation scopes. Section 3 describes the annotation process of the ArNegSpec corpus and shows its annotation results. Section 4 illustrates the proposed approach to handle this problem for the Arabic language in detail. The experiment setup and its evaluation output are detailed in Section 5. Finally, Section 6 concludes this study and proposes future work.

2. Related Work

The motivation to detect the negation and speculation scope was initiated, especially for the English and Spanish languages, using rule-based [15], supervised learning [17], or hybrid approaches [18]. Also, these problems have been studied in other languages, including Chinese, French, and Brazilian Portuguese [11].

Most of the Arabic studies handled these phenomena as a part of their ANLP tasks using the rule-based approach. The negation problem was studied in various Arabic Sentiment Analysis (ASA) systems. Duwairi and Alshboul listed the common negation cues in the MSA and then categorized them into two groups: cues that immediately appear before verbs and the other group only includes ليس cue. As a result, six rules were formulated based on this list to investigate the impact of the negation phenomenon on the MSA texts in the review domain [19]. In another study, El-Naggar et al. added two features to their features list related to the negation for the MSA and Egyptian dialect [20]. These features are an indicator for the negation term in addition to the number of affected words. Both studies in [19] and [20] proposed different solutions to handle the negation phenomenon in the ASA task; however, their impact on the system's performance was not explicitly stated. Later, four advanced rules were proposed to address the negation detection task in the Saudi dialect, which enhanced the performance of the ASA task by 3% in terms of classification accuracy [21]. In 2017, Mostafa proposed an algorithm to detect negation, which depends on a lexicon of the common negation terms in the MSA and DA forms [22]. It identifies the negation cues and then searches for the polarity terms in all the tokens after this negation cue. This algorithm may flip the weight of each token in case of being affected by a negation cue and then pass them to the classifier to reduce the false positives and negatives. Kaddoura et al. proposed a classification algorithm that flips the sentiment of the preceding phrase when a negation cue precedes an opinionated word [8]. This algorithm enhanced the accuracy of the system by 20%.

Despite the performance gain presented in these experimental studies [8], [21], the negation and speculation linguist features cannot be addressed using the simplistic approaches for morphologically and syntactically rich language, Arabic, which has various categories and dialects [23], for several reasons: (1) a negation cue may flip the sentiment of the opinionated phrase it precedes, but in other unusual cases it may confirm the sentiment, (2) the implicit form of negation has not been handled [11], (3) the rare cases such as the affected tokens before as cue, especially in the speculation, are not studied. Therefore, other research works addressed these problems in the Arabic language using sophisticated supervised learning systems. Al-Khawaldeh suggested a Deep Neural Network (DNN) model to identify the negation and speculation in Arabic biomedical data [24]. Moreover, in another study, she addressed this problem with an attention-based neural network with constituency and dependency features to detect the speculation scope [25]. In 2021, a BiLSTM model with FastText word embeddings and the cues and scope features were proposed for detecting the negation scope in Arabic [16]. The experimental results of the deep learning models in the previous three studies achieved remarkable performance in handling these important linguistic features.

The scarcity of corpora annotated with negation and speculation for the Arabic language alleviates the progress of handling the negation and speculation phenomena using supervised learning techniques in comparison to other languages [26]. Due to the fact that negation and speculation are language-dependent phenomena, the grammatical structures of negation and speculation in the Arabic and English languages are different [11]. Other languages' negation- and speculation-aware models are not suitable for Arabic texts. Consequently, annotating an Arabic corpus with negation and speculation is necessary. This corpus will enable the researchers to analyze the effect of these phenomena on the different ANLP tasks.

3. ArNegSpec Corpus

Negation and speculation have two forms: implicit and explicit forms. A cue is clearly written in the text in the explicit form, whereas being comprehended in the case of the implicit form without the existence of this cue. Also, they have a scope that influences a part of a sentence or the entire sentence preceded by the negation and speculation cues; therefore, they are interconnected and share similar characteristics [27].

The absence of annotated corpora with negation and speculation in Arabic impedes the progress of using supervised learning or hybrid approaches in detecting the negation and speculation scope. Thus, the Wikipedia sub-corpus of the ArNeg corpus is extended by manually annotating it for speculation [16]. The texts in this corpus were selected from Wikipedia, covering various topics, including education, technology, science, health, geography, and media. According to Table 1, the corpus has 3,000 sentences, with an average sentence length of **24.84** words. This corpus was manually annotated with negation, where **18.17%** of it includes at least one negated phrase. To annotate it for the speculation, a speculation cue must be identified at first, then its scope, as in the negation phenomenon. A cue may involve a single token or a set of compound tokens [28]. Then, the scope comprises tokens affected by a cue, which may contain tokens before and after this cue.

Table. 1: Corpus Statistics

Sentences	**3,000**
Tokens	**74,495**
Vocabulary	**16,525**
Avg. Sentence Tokens	**24.84**

Annotation guidelines should be followed to annotate the corpus for speculation as the guidelines written for the BioScope [7] and SFU Review [26] corpora. The Arabic annotation guidelines for the speculation in this work [27] are applied. The guidelines adhere to the min-max strategy, in which the smallest unit expressing a speculative meaning will be annotated as a speculation cue. In contrast, the speculation scope is the longest sequence of words that a speculation cue affects. Most of the speculation scopes are aligned from the cue's left side till the end of the sentence or the phrase. The applied guidelines also include the implicit form of speculation in Arabic in case it exists in the corpus. The entire corpus will be annotated for speculation by two native Arabic speakers after explaining the guidelines. Sentences with a negation cue may or may not be negation instances; however, it may be an

indicator for a speculation instance. So, the annotators must carefully handle sentences with negation cues.
INCEpTION annotation platform is utilized for the annotation process, combining machine learning capabilities to actively guide the annotators [29]. In addition, the annotators are trained on the annotation tool to best use its features like automation and recommenders. Figure. 1 is a screenshot for the annotation screen of INCEpTION that shows negated, affirmed, and speculated sentences.

Figure. 1 Negation and Speculation Cases from INCEpTION.

The Cohen-Kappa Inter-annotation Agreement (IAA) [30] measures the annotation process quality where the IAA for the speculation is 0.95. This value confirms the annotation process's reliability; however, it shows that the annotation of the speculation is more difficult than the negation in Arabic, where Cohen's Kappa IAA for the negation is of value 0.98 [16]. A linguist annotated the sentences with disagreements between the two annotators, where most of them were implicit speculation instances.

Table 2 shows that the percentage of the negation and speculation scope in the ArNegSpec corpus are almost the same, with values of **18.17%** and **19.37%,** respectively. The average scope length for both the negation and speculation shows that the scope length is about **32%** of the average sentence length, as in Table 1. Nevertheless, the average scope length for the speculation is larger than the length of the negation scope. This was observed in the annotation process because most of the speculation scope spans to the end of the sentence.

Table. 2: ArNegSpec Corpus Statistics

Negation	
Negated Sentences	**545 (18.17%)**
Avg. Cues per Sentence	**1.27**
Avg. Scope Spans	**7.19**
Speculation	
Speculated Sentences	**581 (19.37%)**
Avg. Cues per Sentence	**1.21**
Avg. Scope Spans	**8.91**

Table 3 and Table 4 show the frequency of the negation and speculation cues in ArNegSpec, where لا and أو are the most commonly used cues.

Table. 3: Normalized Negation Cues

Normalized Cue	Frequency
لا	321
غير	108

ليس	102
لم	72
عدم	46
دون	19
ما	16
إن	4
لن	2
ضد	1

Table. 4: Normalized Speculation Cues

Normalized Cue	Frequency
او	463
قد	154
غالبا	30
اما	13
مابين	12
يمكن – ربما	7
سواء – عادة	3
شك – هل	2
يعتقد – يشار – تبدو – نادرا – إن لم - احيانا	1

4. Proposed Approach

This section explains the proposed approach for detecting the negation and speculation scope in Arabic. The proposed approach considers this problem a sequence classification where each sentence's token is classified as either a part of the scope, a cue, or out of the scope. The Beginning, Inside, Output (BIO) tagging is utilized to label each token in a sentence where the proposed approach detects the cues and their scopes in one single step for the negation and speculation detection tasks. Table 5 shows two different samples for the BOI tagging of a negated and speculated sentence of the Wikipedia corpus. Beginning of the scope (B-Scope) means that this token is the starting token for a scope, Inside the Scope (In-Scope) means that this token is in the middle or the end of the scope, Outside of the scope (O) means that this token is not in the scope, and finally, cue expresses a negation or speculation cue.

Table. 5: Sentence Data Labeling

Phenomenon	Tokens	Labels
Negation	العبرة	O
	بالقيمة	O
	وليس	Cue
	الكم	B-Scope
	والعمق	In-Scope
	اهم	In-Scope
	من	In-Scope
	مجرد	In-Scope
	التغطية	In-Scope
Speculation	تُعتبر	B-Scope
	احيانا	Cue
	غير	In-Scope
	جميلة	In-Scope
	لبعض	In-Scope
	الاشخاص	In-Scope
	التقليديين	

The preprocessing phase greatly impacts the performance of the NLP tasks [31]. Therefore, the input Arabic sentences are cleaned from the stop words, punctuation, Tatweel, and any extra white spaces. Then Tashkeel symbols are stripped in addition to normalizing the hamza characters. Subsequently, a matrix with 3,000 rows contains the preprocessed corpus, where each sentence is represented as a set of tokens. Similarly, the BIO tagging scheme is applied to label the output annotated sentences for negation and speculation. Since the length of each sentence in the corpus is not fixed, padding special [PAD] tokens are appended according to the maximum length of a sentence. Furthermore, each sentence is appended with a special token [CLS]; this token is used for sequence classification tasks. Finally, another special token [SEP] is added as an indicator for the end of the sentence.

Recently, the transformer-based language models proved their strength in language understanding, enhancing the performance of various NLP tasks, including sequence classification tasks. These language models use a self-attention technique to learn the long-range relationships between words, which is advantageous for the scope detection problem. For example, BERT is a language-specific based model which is pre-trained on a huge corpus. BERT employs the transformer architecture to learn the word representation using both the left and right word contexts in a bidirectional manner. As shown in figure 2, the BERT model is fine-tuned with the BiLSTM-CRF layers to detect both the negation and speculation. First, the BERT model takes the tokenized input and then represents each token in the sentence as an embedding representation (Ei). Subsequently, the transformer block computes the score (Ri) that represents each token's contextualized value with respect to all surrounding tokens.

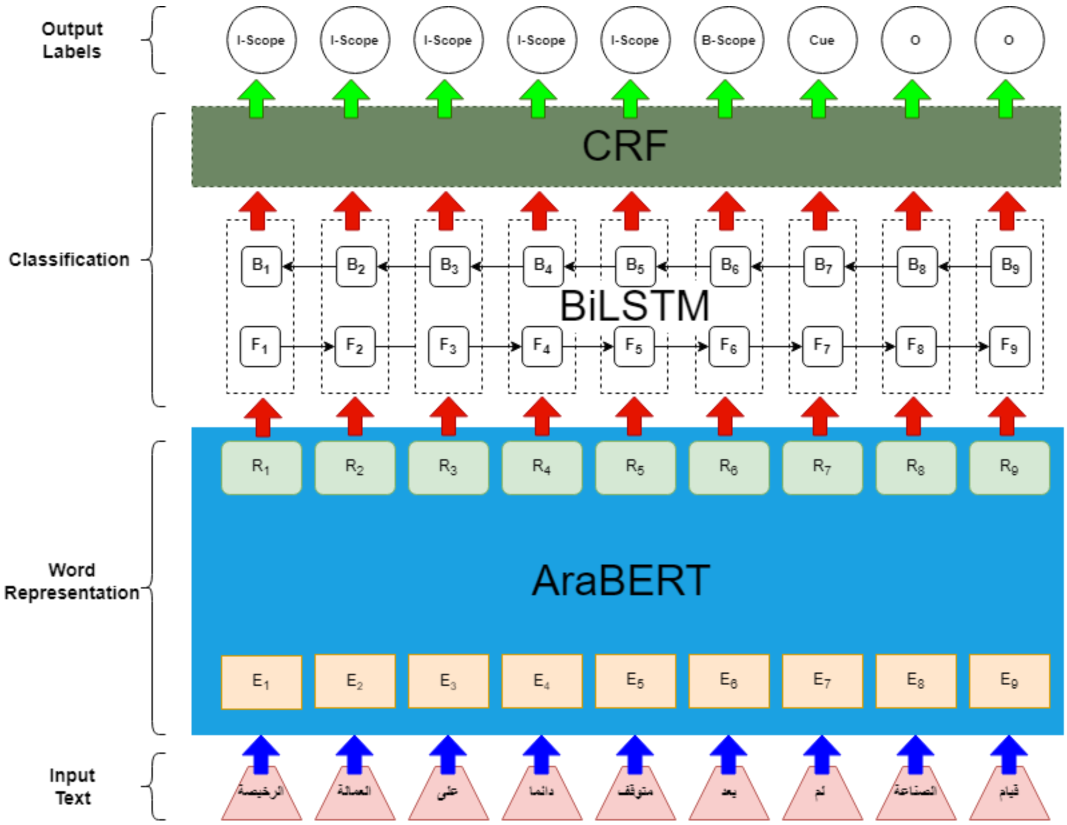


Figure. 2: Transformer-based Negation and Speculation Scope Detection

The predicated representation R_i for each token then feed the BiLSTM-CRF classification layers. The BiLSTM-CRF model proves its outstanding performance in sequence classification tasks [14] where it can predict the scope either that precedes or follows the cue. The BiLSTM layer uses forward (F_i), and backward (B_i) phases that capture the surrounding words' contexts to infer the probabilities of each label. Then, the CRF layer predicts the output labels based on the highest prediction scores. The specially added tokens ([PAD], [CLS], and [SEP]) are removed to show only the predicated output BIO label for each token.

5. Experimentation and Results

This section shows the experiments that evaluate the proposed approach in detecting negation and speculation scope. At first, the ArNegSpec corpus is imbalanced because the percentage of the sentences that includes negation and speculation cases are 18% and 19%, as presented in Table 2. Therefore, there is a need to fix this problem by oversampling the negated and speculated cases to make their percentages near to the percentage of the affirmed sentences. In the case of the negation annotation, the affirmed instances, 2,455 sentences, were extracted and then replicated the 545 negated instances to be near the affirmed cases. Likewise, the same process is applied to speculated sentences. The corpus is partitioned into 80% for the training phase, 10% for the validation, and the remaining 10% for the testing.

The AraBERT[1] language models are utilized as contextualized embeddings to carry out the negation and speculation scope detection [32]. It used the BERT base configuration with a total number of ~110M parameters to build the language model using 70 million Arabic sentences. The authors of AraBERT proposed different versions of their language model where AraBERTv0.x is a non-segmented text while AraBERTv.x relies on a segmented text. In addition, there are two versions of the AraBERT model, base and large; therefore, four combinations of the AraBERT have been utilized.

All the experiments are conducted on a CentOS 7.9-based machine with an NVIDIA V100 GPU with 32 GB of GPU memory. This machine supports Python 3.6.13 and Keras[2] 2.6.0 with backend TensorFlow[3] 2.6.2. We tried different values for the training parameters to perform these experiments. The parameters' values with the best performance were settled with a sequence length of value 96, batch size of 64, dropout of 0.4, and the number of epochs of 20. To fine-tune the AraBERT models to the sequence classification problem, the values of 96 as a sequence length and 4 hidden layers are selected.

The viability of the proposed approach is assessed using various evaluation measures. First, the traditional Precision (P), Recall (R), and F1 measure are used to evaluate the token-level performance. Moreover, the Percentage of Correct Scope (PCS) measure evaluates how the proposed approach accurately predicted the scope as defined in Eq. (1).

$$PCS = \frac{Number\ of\ the\ correctly\ predicted\ scope}{\text{Number of annotated scopes}} \tag{1}$$

[1] https://github.com/aub-mind/arabert
[2] https://keras.io/
[3] https://www.tensorflow.org/

Table 6 shows the cue identification and scope detection evaluation results for the negation and speculation phenomena. These results demonstrate the effectiveness of the proposed approach in handling negation and speculation in Arabic. The best-performing models for the negation cues identification were obtained using either the base or Large-AraBERT-v02; these models obtained an F1 measure of value **98%**. On the other side, the best-performing model for identifying the speculation cue is the Large-AraBERT-v02 with an F1 measure of value **98%**. Hence, the Large-AraBERT-v02 model achieved the same F1 measure for negation and speculation because most negation and speculation cues are single tokens. However, the performance of the Base-AraBERT-v02 in the negation cue identification is better than the speculation cue identification because some negation cues may be considered a speculation cue or included with the speculation cue.

Table. 6: Evaluation of the Proposed Approach for Negation and Speculation Scope Detection

Model	Cue						Scope							
	Negation			Speculation			Negation				Speculation			
	P	R	F1	P	R	F1	P	R	F1	PCS	P	R	F1	PCS
Base-AraBERT-v2	0.93	0.87	0.90	0.90	0.86	0.88	0.76	0.74	0.75	0.71	0.67	0.66	0.66	0.68
Large-AraBERT-v2	0.92	0.85	0.89	0.90	0.86	0.88	0.67	0.70	0.69	0.82	0.67	0.64	0.66	0.55
Base-AraBERT-v02	**0.97**	**0.99**	**0.98**	0.96	**0.98**	0.97	**0.93**	**0.96**	**0.95**	**0.96**	0.93	**0.96**	0.94	**0.96**
Large-AraBERT-v02	**0.97**	**0.99**	**0.98**	**0.99**	0.96	**0.98**	**0.93**	0.95	0.94	0.92	**0.95**	0.94	**0.95**	0.94

The best-achieved results are **bold** formatted.

Likewise, the BERT-based BiLSTM-CRF proposed approach performed well in the negation and speculation scope detection tasks. The best performance for negation scope detection is obtained using the Base-AraBERT-v02 with an F1 measure of **95%,** which outperforms the proposed approach in the previous work by **6%** [16]. Furthermore, this model achieved a PCS of value **96%,** which shows how well the proposed approach recognized the exact negation scope. On the other hand, the best-performing model for the speculation scope detection is the Large-AraBERT-v02 which achieves an F1 measure of **95%** and PCS value of **94%**.

The results show that the non-segmented AraBERT models outperform the segmented versions of the same language model for both cue and scope detection tasks. For example, in the speculation detection task using the base AraBERT models, the performance difference in cue identification is 6% while being 26% in scope detection. In addition, there is a fact that the number of tokens for the segmented AraBERT models is 60K compared to 64K for the non-segmented models. This means that the extra 4K tokens allow further pre-training, improving the overall text representation.

6. Conclusion and Future Work

This study presents the negation and speculation scope detection problems in the Arabic language, in addition to highlighting their impact on the ANLP tasks. The ArNeg corpus, which was annotated with negation, is extended to annotate it with speculation to build the ArNegSpec corpus. This corpus enabled us to study the negation and speculation scope detection in Arabic. Therefore, a transformer-based BiLSTM-CRF approach is proposed to detect the negation and speculation scope. The AraBERT is fine-tuned to be utilized in this sequence classification task. We used four models of the AraBERT to compare their performance in detecting negation and speculation. The results showed that the AraBERT-v02 with BiLSTM-CRF was the best-performing model and achieved an F1 measure of value 95% for both the negation and speculation scope detection. Also, the PCS measure is recorded with a value of 96%, which demonstrates the effectiveness of the proposed approach.

The future goals are to annotate this corpus's negation focus and study its effect on the detection system. Additionally, more transformer architectures will be fine-tuned with other classification layers to detect the negation and speculation scope with the highest performance measure. Therefore, this gives the research community a chance to use these models in enhancing the results of the different ANLP tasks.

Acknowledgment

All experiments were carried out on the Aziz Supercomputer; therefore, we would like to thank the management of the High Performance Computing (HPC) Center at King Abdulaziz University.

References

1. A. Alsayat and N. Elmitwally, A comprehensive study for Arabic Sentiment Analysis (Challenges and Applications), Egyptian Informatics Journal. 21(1) (2020) 7–12.
2. iSarcasmEval: Intended Sarcasm Detection In English and Arabic. https://sites.google.com/view/semeval2022-isarcasmeval, 2022 (accessed 02 October 2022).
3. A. Elnagar, S. M. Yagi, A. B. Nassif, I. Shahin, S. A. Salloum, Systematic Literature Review of Dialectal Arabic: Identification and Detection, IEEE Access. 9 (2021) 31010–31042.
4. N. Y. Habash, Introduction to Arabic natural language processing, 1st ed., Morgan and Claypool Publishers, 2010.
5. Oxford Learner's Dictionaries, Negation Definition. https://www.oxfordlearnersdictionaries.com/definition/english/negation?q=negation, (accessed 02 October 2021).
6. Oxford Learner's Dictionaries, Speculation Definition. https://www.oxfordlearnersdictionaries.com/definition/english/speculation?q=speculation, (accessed 06 October 2022).
7. V. Vincze, G. Szarvas, R. Farkas, G. Móra, J. Csirik, The BioScope corpus: biomedical texts annotated for uncertainty, negation and their scopes, BMC Bioinformatics. 9(11) (2008) Suppl 11-S9.
8. S. Kaddoura, M. Itani, C. Roast, Analyzing the Effect of Negation in Sentiment Polarity of Facebook Dialectal Arabic Text, Applied Sciences. 11(11) (2021) 4768.
9. N. Pröllochs, S. Feuerriegel, B. Lutz, D. Neumann, Negation scope detection for sentiment analysis: A reinforcement learning framework for replicating human interpretations, Information Sciences. 536(2) (2020) 205–221.
10. K. Baker et al., Modality and Negation in SIMT Use of Modality and Negation in Semantically-Informed Syntactic MT, Computational Linguistics. 38(2) (2012) 411–438.
11. A. Mahany, H. Khaled, N. S. Elmitwally, N. Aljohani, S. Ghoniemy, Negation and Speculation in NLP: A Survey, Corpora, Methods, and Applications, Applied Sciences. 12(10) (2022) 5209.
12. S. M. Jiménez-Zafra, R. Morante, M. Martin, L. A. Ureña-López, A review of Spanish corpora annotated with negation, in 27th International Conference on Computational Linguistics, 2018, p. 915–924.
13. S. Lima, N. Perez, M. Cuadros, G. Rigau, NUBES: A Corpus of Negation and Uncertainty in Spanish Clinical Texts, in LREC 2020 - 12th International Conference on Language Resources and Evaluation, 2020, p. 5772–5781.
14. C. Dalloux et al., Supervised learning for the detection of negation and of its scope in French and Brazilian Portuguese biomedical corpora, Natural Language Engineering. 27(2) (2021) 181–201.

15. W. W. Chapman, W. Bridewell, P. Hanbury, G. F. Cooper, B. G. Buchanan, A simple algorithm for identifying negated findings and diseases in discharge summaries, Journal of Biomedical Informatics. 34(5) (2001) 301–310.
16. A. Mahany et al., Supervised Learning for Negation Scope Detection in Arabic Texts, in Tenth International Conference on Intelligent Computing and Information Systems (ICICIS), 2021, p. 177–182.
17. O. Solarte Pabón, O. Montenegro, M. Torrente, A. Rodríguez González, M. Provencio, E. Menasalvas, Negation and uncertainty detection in clinical texts written in Spanish: a deep learning-based approach, PeerJ Computer Science. 8(6) (2022) e913.
18. W. Packard, E. M. Bender, J. Read, S. Oepen, R. Dridan, Simple Negation Scope Resolution through Deep Parsing: A Semantic Solution to a Semantic Problem, in Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics, 2014, p. 69–78.
19. R. M. Duwairi, M. A. Alshboul, Negation-Aware Framework for Sentiment Analysis in Arabic Reviews, in 3rd International Conference on Future Internet of Things and Cloud, 2015, p. 731–735.
20. N. El-Naggar, Y. El-Sonbaty, M. A. El-Nasr, Sentiment analysis of modern standard Arabic and Egyptian dialectal Arabic tweets, in Computing Conference, 2017, p. 880–887.
21. A. Assiri, A. Emam, H. Al-Dossari, Towards enhancement of a lexicon-based approach for Saudi dialect sentiment analysis, Journal Information Science. 44(2) (2018) 184–202.
22. A. M. Mostafa, An automatic lexicon with exceptional-negation algorithm for arabic sentiments using supervised classification, Journal of Theoretical and Applied Information Technology. 95(15) (2017) 3662–3671.
23. M. Abdelazim, W. Hussein, N. Badr, Automatic Dialect identification of Spoken Arabic Speech using Deep Neural Networks, International Journal of Intelligent Computing and Information Sciences. In Press.
24. F. T. Al-khawaldeh, Speculation and Negation Detection for Arabic Biomedical Texts, World of Computer Science and Information Technology Journal. 9(3) (2019) 12–16.
25. F. T. Al-Khawaldeh, Hierarchical Attention Generative Adversarial Networks for Biomedical Texts Uncertainty Detection, International Journal of Advanced Studies in Computer Science and Engineering. 8(6) (2019) 1–12.
26. N. Konstantinova, S. C. M. de Sousa, N. P. Cruz, M. J. Maña, M. Taboada, R. Mitkov, A review corpus annotated for negation, speculation and their scope, in 8th International Conference on Language Resources and Evaluation, 2012, p. 3190–3195.
27. A. Mahany, H. Khaled, N. S. Elmitwally, N. Aljohani, S. Ghoniemy, Annotated Corpus with Negation and Speculation in Arabic Review Domain: NSAR, International Journal of Advanced Computer Science and Applications. 13(7) (2022) 38–46.
28. C. Dalloux, V. Claveau, N. Grabar, Speculation and Negation Detection in French Biomedical Corpora, in Natural Language Processing in a Deep Learning World, 2019, p. 223–232.
29. J. C. Klie, M. Bugert, B. Boullosa, R. E. de Castilho, I. Gurevych, The INCEpTION Platform: Machine-Assisted and Knowledge-Oriented Interactive Annotation, in 27th International Conference on Computational Linguistics: System Demonstrations, 2018, p. 5–9.
30. J. Cohen, A Coefficient of Agreement for Nominal Scales, Educational and Psychological Measurement. 20(1) (1960) 37–46.
31. M. Salim, S. Saad, M. Aref, Preprocessing the Egyptian Arabic Dialect for Personality Traits Prediction, International Journal of Intelligent Computing and Information Sciences. 19(1) (2019) 1–12.

32. W. Antoun, F. Baly, H. Hajj, AraBERT: Transformer-based Model for Arabic Language Understanding, In 4th Workshop on Open-Source Arabic Corpora and Processing Tools, with a Shared Task on Offensive Language Detection, 2020, p. 9–15.