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Emotion Detection Based on Sentiment Analysis: An Example of a Social Robots on Short and Long Texts Conversation

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Abstract:

Purpose: *The aim of this paper is to present a solution to detect emotions from text obtained in a conversation with a social robot. Emotions will be detected using sentiment analysis based on the English and Polish lexicon.*
Design/methodology/approach: *Data from social robot conversation records will be converted into text and then split into short and long speech. The original language utterances will then be analysed using the Polish lexicon, while the translated texts will be analysed using the English emotional lexicon.*
Findings: *The results obtained indicate the same or similar distribution of emotions made by sentiment analysis using both plNetWord and NRC lexicons.*
Practical Implications: *The results obtained can be used for further research addressing the creation and development of lexicons based on the selected language. They are also applicable to the implementation of solutions for detecting and responding to conversational emotions by social robots.*
Originality/Value: *The analyses so far mostly take up the subject of textual analysis in English. The aim of the present study is to analyse a Polish text and to compare the results obtained with those for English texts. The analysis of differences in the emotional sentiment of utterances may lead to the construction of more effective models based on the chosen language.*

Keywords: *Sentiment analysis, emotion detection, social robots.*

JEL classification: *D12, D47, D53.*

Paper type: *A research study.*

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1. Introduction

Texts derived from conversation are characterised by significant variation compared to continuous texts derived from blog posts, social networks or journalistic reporting. Conversational text poses a challenge in the context of emotion analysis because as the conversation unfolds, there can be a change in the intensity of both a particular emotion and several emotions at once. An additional difficulty is also the length of the utterance, which is very often short. A single analysis of a short utterance may not allow to determine the correct sentiment of the sentence, and only an analysis in the context of the conversation has a chance to highlight this context and this emotion.

The analysis of conversational sentiment is useful from the point of view of many areas of analysis (Agarwal and Toshniwal, 2018). It can be applied to statements related to finance, economics, everyday conversations, or, as in the case under review, based on conversations with a social robot.

The aspect of language analysed is also particularly relevant here. While image analysis allows for universal solutions that can be applied almost independently of the cultural context, yes, text analysis is strictly dependent on the language in which it is written and the cultural context. It is this significant difference that makes the vast majority of studies on sentiment analysis and emotion detection rely on lexicons and analyse English texts. The universality and ubiquity of this language has allowed the creation of many advanced methods to detect and recognise emotions in utterances (Burnap *et al.*, 2015).

However, such popularity is not enjoyed by other languages, for which individual lexicons have to be created anew. Some approaches propose to translate the analysed texts into English and then process them using the available methods. Other researchers suggest creating lexicons dedicated to a particular language, including both emotional valence and word interrelationships (Kiritchenko, Zhu, and Mohammad, 2014).

In this paper, the analysed texts coming from conversations with social robots will be analysed both in terms of a solution dedicated to the Polish language, will be translated and then analysed by a solution available from the English language.

2. Literature Review

Based on the conducted analysis of theoretical reports, many researchers have taken up the topic of detecting and analysing the sentiment of utterances using lexicons. The main reason for such research is the phenomenon that the emotional information conveyed by the sender is distributed more in the text/voice channel than in the visual channel. This means that although many effective methods are available to detect emotion based on image/video, it may be an insufficient source and may not allow for a deeper analysis of an individual's emotions.

The extreme difficulty of combining the two approaches is also pointed out, as well as the phenomenon of confusing emotion analysis between listener and sender and the difficulty of distinguishing between the utterances of the individuals in question during sentiment analysis. It should also be noted that the analysis of text in relation to the analysis of sound leads to simplification and reduction of a lot of information that sound carries.

Based on the text it is not possible to notice modulations, pauses or changes in the tone of voice. Nevertheless, this represents an important and needed solution, as these types of records are widely used in both social networks and streaming platforms. Within the available solutions, some trends can be observed, which are systematically developed.

One of the most widely developed solutions is the approach using Deep learning methods (Gu *et al.*, 2018). The use of neural networks to process and analyse emotions is one of the most popular solutions. Such methods, with particular emphasis on LSTM Networks and R-CNN Networks, are used in image analysis and in some work on text analysis. They allow satisfactory performance for given classes of observations. In the context of text analysis, one of the biggest challenges is to ensure a sufficiently large and diverse dataset. As mentioned earlier, image analysis can be carried out almost independently of the cultural and linguistic context. Which means that the same data sets can be used to train networks that will then be used in a variety of social settings.

However, such a transfer is not possible in the case of text analysis. Text is strictly dependent on the language in which it is written. This means that for a specific language, it would be necessary to create a large enough database to train a network that would recognise, for example, Polish conversation. This is not an impossible task, but it requires time and money due to the lack of currently available databases that would have a representative sample of data for the given emotional categories.

Another branch developed in the field of emotion detection are methods that do not use neural networks, but make use of machine learning solutions (Dhaoui, Webster, and Tan, 2017). These work by searching for specific features and then creating appropriate representations from them to be applied to classification methods. Many researchers undertake such work using SVM method, Naive Bayes Method or Decision Trees Method.

According to research, such a solution allows the detection of a wide range of solutions, but for a number of reasons it often has a lower accuracy than other solutions. The main reason for this is the exceptional multimodality of the display of emotions, which is realised through many channels, such as image, sound, text of utterance, but also the absence of utterance or the use of emoticons (Khoo and Johnkhan, 2018). Such diversity leads to difficulties in accurately classifying a given emotion.

The last type of research that is conducted in the context of sentiment analysis is rule-based approaches (Drus and Khalid, 2019). They are based on the comparison of the obtained data to sets containing already once described data together with the assigned emotion (Muhammad, Kusumaningrum, and Wibowo, 2021; Sadia, Khan, and Bashir, 2018). The main disadvantage of these approaches is the necessity to have or develop a given lexicon, i.e. a reference to which the data will be compared. What is important, a given lexicon is dependent on the language analysed, which translates into a multitude of lexicons for English and their underrepresentation for other languages (Khan *et al.*, 2016). It is this approach that will be presented later in the study, where both Polish and English lexicons will be used.

3. Materials and Methods

In order to achieve the set objectives, the paper uses two lexicons and a collection of human-robot conversations divided into short and long conversations.

The first lexicon used was the NRC Emotional Lexicon, which was created in 2011, and Amazon's Mechanical Turk solution was used as the annotation method (Mohammad and Turney, 2013). The dictionary that served as a base for the analysed words was the 1911 Roget Thesaurus. This thesaurus allows grouping related words into categories that have similar contexts or sense of expression. Importantly, if a word can be assigned to more than one category, it is marked as ambiguous and has more than one meaning.

Based on this solution, a near-synonyms system was then developed, which allowed synonyms to be assigned to a word. The system created had a certain degree of randomisation. The material thus prepared was then evaluated by annotators, who rated the synonyms presented to them. The developed lexicon consists of about 24 thousand pairs of words of similar meaning. These word pairs were then used to elaborate emotional connections and to create a proper lexicon of emotional connections consisting of 14 thousand word types. It allows to identify negative or positive sentiment and to detect 8 different emotions such as anger, anticipation, disgust, fear, joy, sadness, surprise and trust.

Another lexicon used was the Polish plWordNet lexicon (Janz *et al.*, 2017; Rudnicka *et al.*, 2019). This is a lexicon based on Princeton WordNet in English, and the version used was 4.2. It consists of over 224 thousand words divided into verbs, nouns, adverbs and adjectives. The network allows for the study of emotional collocations, i.e. frequently occurring connections between words with emotional overtones. The resulting lexicon consists of approximately 180,000 words having an emotional annotation to one or more emotions.

The lexicon makes it possible to identify basic emotions such as joy, trust, looking forward to something expected (anticipation), sadness, anger, fear, disgust and surprise at something unexpected (Maziarz *et al.*, 2016). In addition to emotions, it is possible to detect universal values such as usefulness, the good of others, truth, knowledge, beauty, happiness, non-usefulness, harm, ignorance, error, ugliness, unhappiness. In addition, the lexicon makes it possible to identify emotional attitudes, i.e., values ranging from strongly negative to strongly positive. It also takes into account neutral and weakly negative and positive attitudes.

3.1 Conversation Data

In order to test and analyse emotional sentiment, a recording was made of 80 conversations with a social robot having a chat bot option implemented, which is devoid of emotion and shows only neutral statements. This approach made it possible to partially overcome the difficulty shown by other researchers, i.e., distinguishing the emotions of the sender from the listener. Conversations were further divided into long and short ones. The criteria for short conversations were taken to be 8 - 10 messages coming from both sides, which on average translated into 4 messages from the person talking to the social robot.

Long conversations, on the other hand, were taken to be more than 16 messages till 30 messages, which on average allowed the analysis of 14 utterances from the person. Utterances between 11 and 15 messages were treated as medium length and were not analysed in the study. This made it possible to obtain 36 short messages, 31 long messages and 13 medium messages. The long and short messages were then translated into English from the Polish language in order to be analysed using the English lexicon.

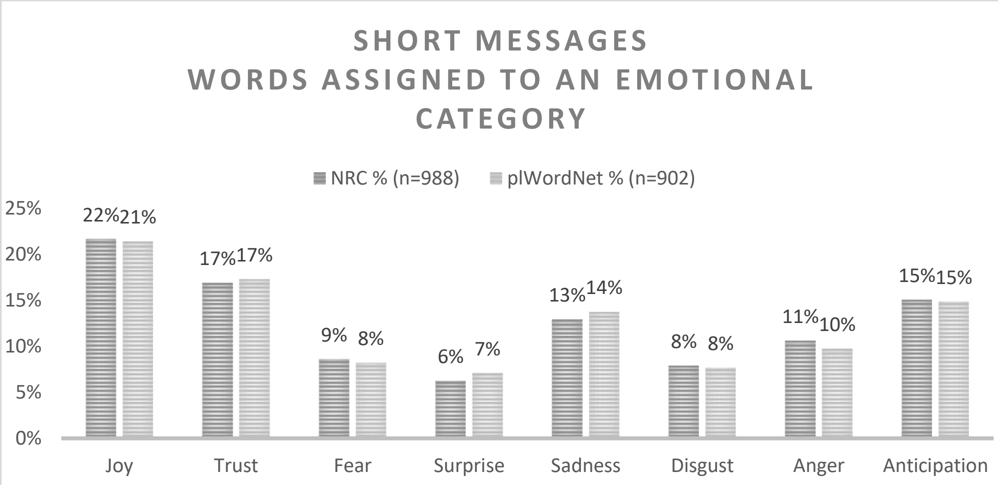
4. Results

Thirty-six short and 31 long messages were developed for analysis. Each set was compiled in Polish and English. The short messages contained a total of 1724 words in Polish and 1604 words in English. The analyses showed that the short messages contained 988 emotionally charged Polish words and 1027 emotionally charged English words. The long messages contained 21786 Polish words and 13449 emotionally charged Polish words.

In English there were a total of 20441 words for long messages and 14211 emotionally charged words. Both lexicon allowed the division of emotionally charged words into 8 categories representing each basic emotion. The obtained results are presented in Figures 1 and 2.

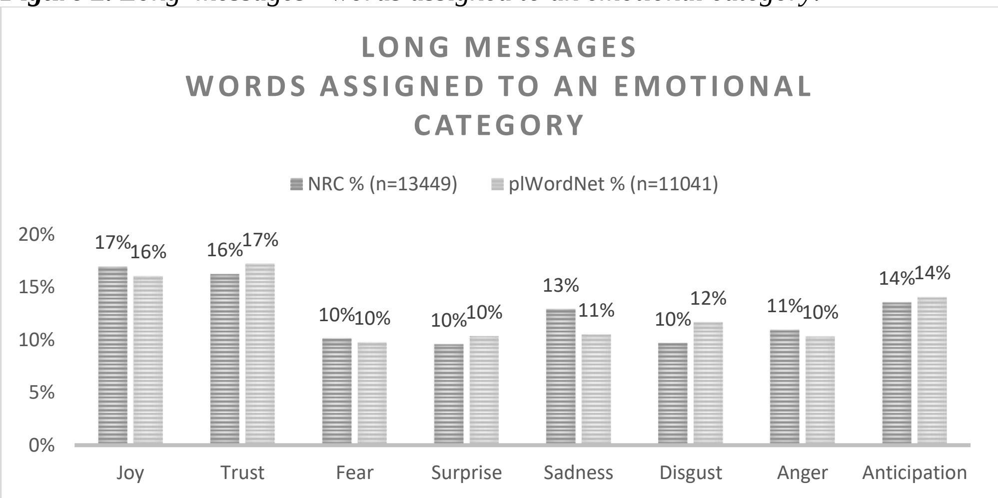
The results obtained for short messages showed no or little discrepancy between the NRC lexicon and plWordNet. Similar results were also obtained for long messages with a maximum discrepancy of 2% for the emotion disgust (NRC=10%, plWordNet=12%) and emotion sadness (NRC-13% and plWordNet=11%).

Figure 1. *Short messages - words assigned to an emotional category.*



Source: *Own elaboration based on research.*

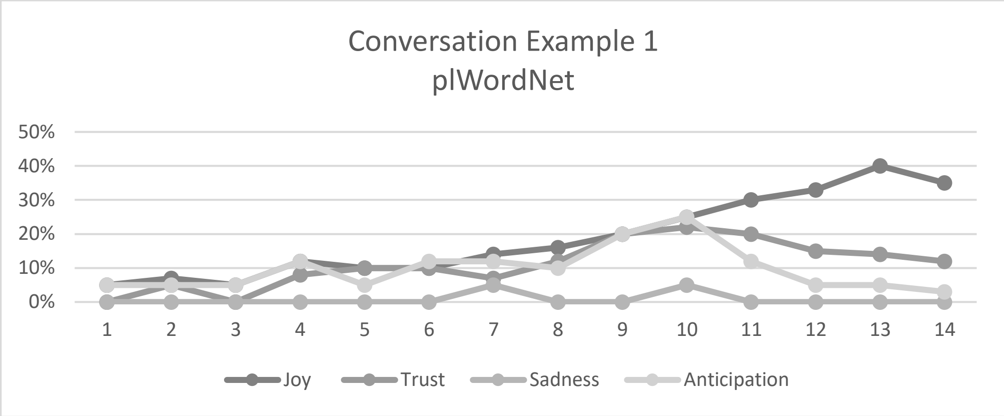
Figure 2. *Long messages - words assigned to an emotional category.*



Source: *Own elaboration based on research.*

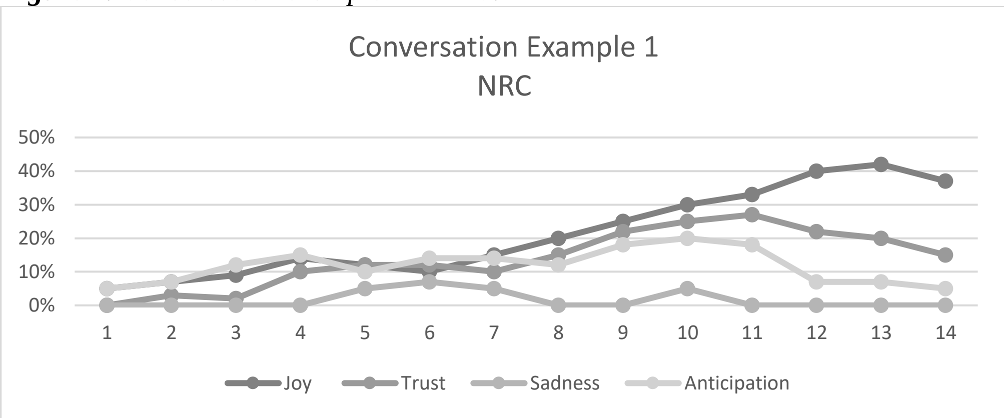
In addition to the results obtained for the pooled analysis of both long and short conversations, changes in conversations based on the individual utterances analyzed were also analyzed. For these analyses 3 examples are presented, both for the analysis of the Polish text based on plNetWord, but also for the English text based on NRC. The examples are presented in Figuress 3 to 8. The first example concerns waiting for the arrival of friends. The second example is about a conversation after failing an exam at university. Example three is about waiting for the publication of the results of admission to a master's degree program.

Figure 3. *Conversation example 1 – plWordNet.*



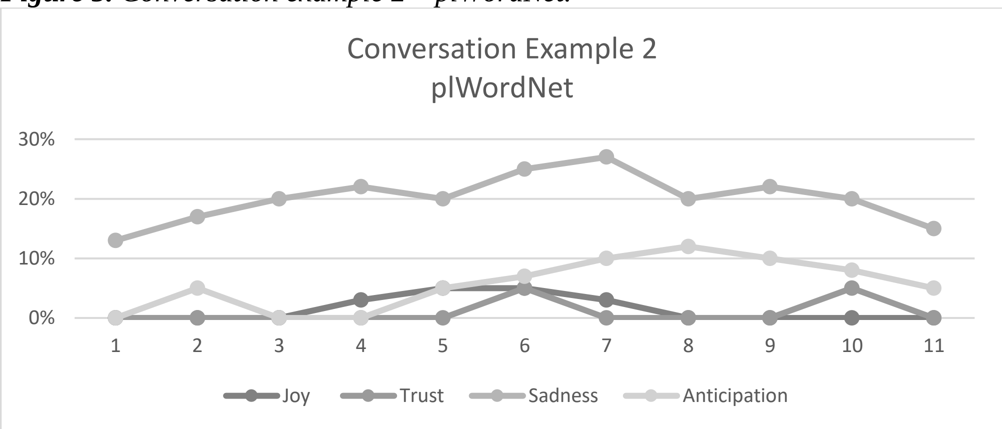
Source: *Own elaboration based on research.*

Figure 4. *Conversation example 1 – NRC.*



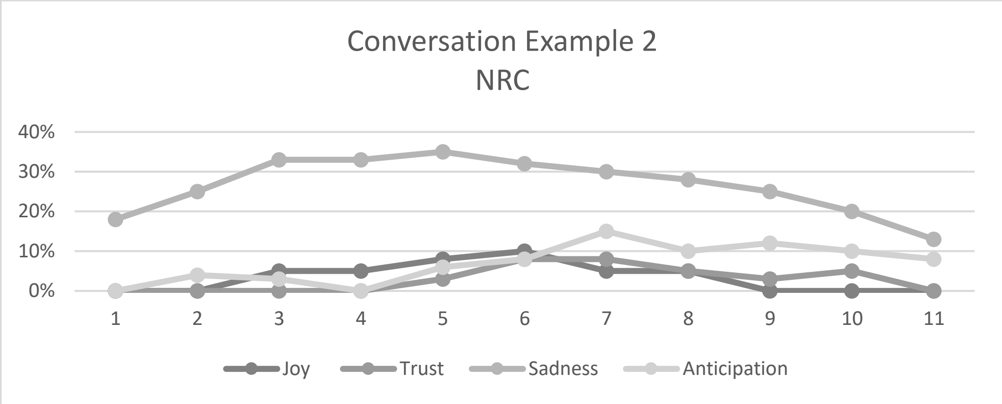
Source: *Own elaboration based on research.*

Figure 5. *Conversation example 2 – plWordNet.*



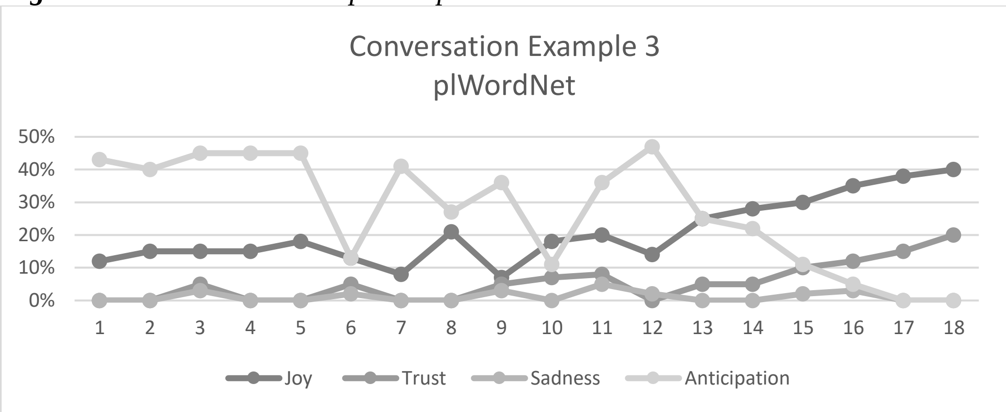
Source: *Own elaboration based on research.*

Figure 6. *Conversation example 2 – NRC.*



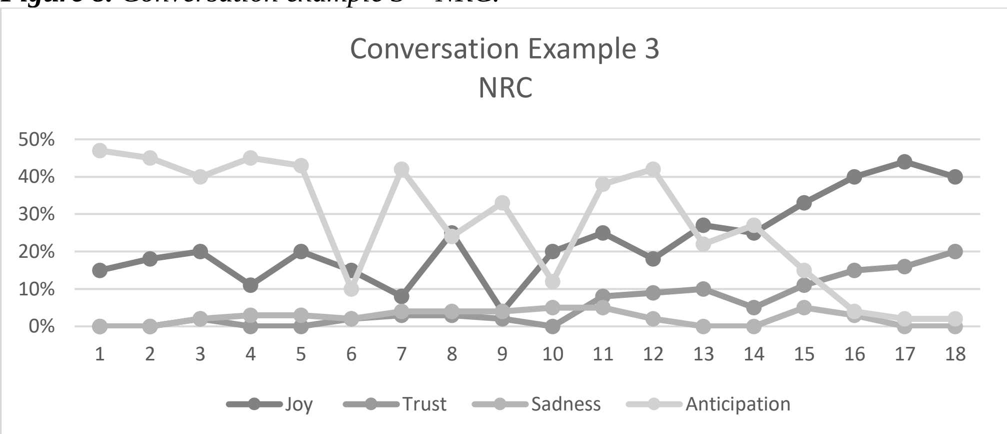
Source: *Own elaboration based on research.*

Figure 7. *Conversation example 3 – plWordNet.*



Source: *Own elaboration based on research.*

Figure 8. *Conversation example 3 – NRC.*



Source: *Own elaboration based on research.*

Based on the examples presented, one can see a replication of the trend associated with the 4 most widely represented emotions, i.e., joy, trust, sadness and anticipation.

5. Discussion and Conclusion

The purpose of this paper was to present sentiment analyses on data derived from conversations held with a social robot. Data were prepared in Polish and English versions, and divided into long and short conversations. Then, sentiment analyses were conducted collectively for short and long conversations taking into account two different lexicons, i.e., NRC and plWordNet. The next step was to perform cross-sectional analyses on the selected long conversations in order to analyze changes in the selected four dominant emotions. The results obtained indicate the same or similar distribution of emotions made by sentiment analysis using both plNetWord and NRC lexicons.

However, the conducted study is not free from some limitations. Firstly, the conducted analyses were carried out on a limited set of conversations, which in further research work will be extended to other types of conversations. For a thorough analysis, a chat bot implemented in a social robot was used to minimize the impact of the listener's speech. Further analysis will be conducted considering conversations between two people. The obtained results also contradict the part of the research that shows the important role of local lexicons created for particular languages.

The results obtained did not allow for a difference analysis because the results obtained showed little variation. Further work is to test these results on a larger sample of data to see if using targeted lexicons for a particular language shows more emotional diversity than when translating texts into English and using available lexicons for English.

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