Performance Analysis of Different Sentiment Polarity Dictionaries on Turkish Sentiment Detection

Ayşe Berna Altınel[1], Kübra Buzlu[2], Kaan İpek[3]

[1] Department of Computer Engineering, Faculty of Technology, Marmara University, Istanbul, Turkey
berna.altinel@marmara.edu.tr

[2] Department of Computer Engineering, Faculty of Technology, Marmara University, Istanbul, Turkey
kubrabuzlu@marun.edu.tr

[3] Department of Computer Engineering, Faculty of Technology, Marmara University, Istanbul, Turkey
kaan-ipek@marun.edu.tr

***Abstract*- In places such as social media and news websites, the number of web-based textual materials those deal with today's events and contain people's emotions continues to increase inevitably day by day. All of these texts, with their own importance, affect our society in some way. For this reason, it is very important to automatically detect the sentiment polarities of these texts. In this study we developed several statistical-based semantic algorithms for Turkish sentiment analysis task. Furthermore, we conducted experiments on sentiment analysis in Turkish texts using different sentiment polarity dictionaries. We perform a number of experiments on some datasets which we collected from Twitter platform. In our experimental environment we also use two dictionaries to get the sentiment polarity score of Turkish terms and phrases: We built the first sentiment polarity dictionary by using a translator and this dictionary includes about 159,876 Turkish words. We built the second sentiment polarity dictionary by using GDELT (Global Data on Events, Languages and Tone) and this dictionary includes about 84,744 Turkish words. We also implement the state of the art baseline algorithms in order to compare the performance results. There are three important outcomes of this study: 1.) We built two publicly available sentiment polarity dictionaries for Turkish, 2.) We developed statistical-based novel semantic algorithms for Turkish sentiment analysis task, 3.) We report the observations of the effect of using different semantic-polarity dictionaries on Turkish sentiment polarity detection problem. Experiment results show that the algorithms we have developed are valuable because they give higher classification performance than the baseline algorithms on Turkish sentiment polarity detection task.**

Keywords—Turkish sentiment analysis, text classification, sentiment polarity, statistical-based semantic algorithms, sentiment polarity dictionaries.

I. INTRODUCTION

As in all languages, Turkish is a language that has its own difficulties due to its agglutinative nature. Considering that last year's internet usage rate was 72% in Turkey, the internet usage with a serious increase reached more than 77% of the Turkish population in 2021 [1]. At this point, the importance of implementing an automated Sentiment Analysis (SA) system has increased significantly.

SA is the contextual mining of a text. It detects, identifies, and extracts properties of texts. SA can be automated using Natural Language Processing (NLP). It has many usage fields; for example, it can be used for classifying the sentiment polarity of a text as positive, negative, or neutral, detecting people's opinions, emotions, or attitudes towards an event or an entity. Consequently, it can be used in many fields such as marketing, politics, social media, etc.

SA has become a popular research topic with the growing usage of social networks. An increasing number of people started to share their opinions on social networks. Data collection is a very important step of these research studies. Especially, studies which use more data, receive more accurate results. However, finding proper data is not usually easy. Furthermore, labelling data is a costly work and requires human experts.

SA has some difficulties. One of them is its dependency on language. The different languages have different levels of difficulties. Turkish has an agglutinative culture which means that words are being created by adding suffixes to the root word. It can change the semantic orientations of Turkish words. Because of the morphology of the Turkish language, finding or creating a Turkish lexicon consisting of every variant of Turkish words is considered impossible. Another difficulty is that Turkish alphabet has some letters which do not exist in the English alphabet. The other difficulty is sentiment lexicons have limited resources. In conclusion, many factors add important challenges to SA in Turkish.

SA can be performed on different levels. These levels are aspect level, document level, sentence level, and word level. In order to perform SA, many approaches can be used. Categories of these approaches are Dictionary-Based, Corpus-Based, Machine Learning (ML) Based, and lastly Hybrid-Based.

This study aims to compare the performance of two dictionaries with different proposed statistical-based seman-

978-1-6654-9810-4/22/$31.00 ©2022 IEEE

2022 International Conference on INnovations in Intelligent SysTems and Applications (INISTA) | 978-1-6654-9810-4/22/$31.00 ©2022 IEEE | DOI: 10.1109/INISTA55318.2022.9894142

tic algorithms for Turkish sentiment polarity detection task. We conducted experiments on two datasets. Then, the classification results of the proposed algorithms were compared with the classification results of the baseline algorithms. According to the experimental results, all of the proposed algorithms are superior to all of the baseline algorithms on most of the test cases. Furthermore, it has been observed that more successful results are obtained with the GDELT dictionary in compare to the Translated dictionary. In addition, in this study, we created two publicly available sentiment polarity dictionaries for Turkish.

The remainder of the paper is organized as follows: similar studies in the field are summarized in Section 2. In Section 3, the suggested algorithms and the dictionaries used in the study are presented. In section 4, the datasets, the baseline algorithms, the experimental setup and experimental results are mentioned. Finally, conclusions and the future directions are given in Section 5.

II. Related Work

Dehkharghani et al. [2] built a comprehensive SA system for Turkish by doing the analysis at different granularity levels. In the study, a subset of the dataset of 60,000 documents was used. They manually labelled 1,000 randomly chosen document and 2,700 sentences from the chosen subset as “positive”, “negative”, or “neutral”. Firstly, they segmented the document into sentences, then they used tokenization. Secondly, they found morphological analysis of each word. Lastly, they assigned polarity scores to words. In conclusion, they obtained 73.42% and 79.06% accuracies in sentence classification task and document classification task. For future work, the analysis can be extended by studying SA deeply at phrase level.

Öztürk et al. [3] made an opinion mining analysis to determine opinions of the public towards the Syrian refugee crisis which has been widely discussed through social media recently. They collected a total of 2,381,297 Turkish and English tweets related to Syrian refugee crises. Since there was not an extensive Turkish lexicon that would satisfy the research, they developed a Turkish sentiment lexicon. The RSentiment Package was used for English tweets. They compared the Turkish and English tweets, then visualized the data. According to the experimental results, 35% of tweets in Turkish have positive sentiment towards the Syrian refugee subject, on the other hand this ratio is 12% in English tweets.

Bayraktar et al. [4] presented a holistic method for Turkish aspect-based SA. As a dataset, they collected many restaurant reviews from various resources. They applied preprocessing steps to the dataset. The Latent Dirichlet Allocation (LDA), C-value, and Web Search Based Feature Extraction (WSBFE) methods were used during the aspect extraction process. Finally, the accuracy received in the aspect extraction was 56.28% and in sentiment classification was 52.05% which is relatively low because of the unpredicted aspect-sentiment pairs. For future work, it is considered that adding the double propagation method to the system.

Kilimci [5] aimed to predict the direction of the Borsa Istanbul index using SA techniques. Two datasets were collected using Turkish and English tweets with the BIST100 and XU100 tags on Twitter. The datasets were enriched by using word embedding methods. Ensemble learning was also used in their study. Convolutional Neural Network (CNN), Recurrent Neural networks (RNN), Long Short-Term Memory (LSTM) algorithms, and MV, STCK methods were used. Firstly, ant colony optimization and feature selection were applied on the dataset. Secondly, the features were embedded. Then, documents were vectorized and classification was performed. Finally, they achieved a classification success of 78.07% in the Turkish dataset and 78.92% in the English dataset.

Aytekin and Keskin [6] proposed a SA method about interest-free finance systems. The analysis was made on Turkish texts. They aimed to detect the positive and negative perceptions of potential customers towards interest-free financial systems The dataset consists of Turkish reviews of customers in January 2019 that was collected from various resources. A sentence level SA was performed. Initially, they specified the most frequently used concepts which are related to the interest-free finance systems. Then, they reviewed the data with the specified keywords. Finally, they classified the texts as positive, negative, or neutral and analyzed the results. To conclude, the fact that “participation banks” and concept of “interest” are mentioned together in the news creates a negative prejudice towards these institutions.

Sarıman and Mutaf [7] have aimed to analyze people’s feelings about COVID-19 through social media using ML methods [21]. They collected 2 million tweets and processed the data. They obtained the sentence analysis, emotion analysis, and the meaning of the tweets. They evaluated the system and used AUC metric as the base metric of success. Labeled classes were Mask, Eba, Curfew, State Support, and Short Working Allowance. They obtained the AUC value, after classifying the tweets as positive and negative. At the end of the study, 97% classification accuracy was achieved for Mask class, 94% classification accuracy was achieved for Eba class, 98% classification accuracy was achieved for Curfew class, 86% classification accuracy was achieved for State Support class and 91% classification accuracy was achieved for Short Working Allowance class.

Tuzcu [8] classified Turkish texts with sentence-level SA. Turkish book reviews about different books were collected from an online book sale website. The data were preprocessed. Different ML algorithms were used. As a result of the research, it was seen that different ML algorithms received different results on the same dataset. To conclude, the algorithm with the highest accuracy rate was the MLP algorithm.

Erşahin et al. [9] presented a hybrid SA approach which consists of dictionary-based and ML approaches. A new lexicon was created by expanding the STN lexicon using the ASDICT model in the dictionary-based approach. The classification problem was handled by using different ML models. Different datasets were used. Datasets contain hotel and movie reviews, and tweets. According to the experimental results of this study, a hybrid approach provides better results on SA task. The system was achieved the highest accuracy which is relatively 83%.

Ayvaz et al. [10] tried to extract meaningful information from a big chunk of data using SA. Existing SA lexicons were analyzed and tried to create a new lexicon using the extracted data from social media. In order to evaluate the efficiency of the created lexicon, the analysis was performed on the data collected from Twitter on specific tags. The analysis was performed on two topics. The topics were the effects of weather change on people's feelings and people's feelings towards a television show called Survivor. According to the experimental results of the first topic's analysis, people tend to be happier in summer months than winter months. According to the experimental results of the second topic's analysis, people who strictly follow the Survivor show tend to share negative emotions towards the Survivor show.

Açıkalın et al. [11] have proposed two algorithms based on the BERT model for SA using different data in Turkish. The first model is a multilingual version of BERT. For the second model, the Turkish texts were translated into English, and then the BERT is run on those textual materials. According to the analysis reported in the study [11]; when sufficient data is obtained, the BERT model can generalize the learned information better.

In the study of Aksu and Karaman [12], SA was made on topics related to touristic areas. For this purpose, two different SA methods were compared from the point of classification accuracies. According to the experimental results obtained from this study, the application of preprocessing to the data has a great role in increasing the classification accuracy of the SA. In order to make this comparison, the effects of preprocessing were analyzed by calculating the accuracy of different ML methods in SA with or without preprocessing. Four different ML classifiers such as Naive Bayes (NB), Multinomial Naive Bayes (MNB), K-Nearest Neighbors (KNN), and Support Vector Machines (SVM) were used from the Weka library for SA task. It has been seen that SVM classifiers have the highest score in this system compared to other classifiers.

III. Methodology

In our study several different approaches and two different dictionaries are presented. The details of the dictionaries and the approaches are given below:

A. Dictionaries

The Polarity (Tone) value used in these dictionaries are used to express the negative or positive polarity of the word. The value itself -1 is interpreted as a negative polarity and a value of 1 is interpreted as a positive polarity. Tone score is not restricted to negative or positive but expresses a mixture of more detailed emotional states such as anger, fear, joy, sadness, kindness, disappointment and excitement. In this study, two different dictionaries were used. These are the Translated dictionary and the GDELT dictionary.

Translated Dictionary:

We have prepared the Translated dictionary by expanding the scope of the SWNetTR dictionary. To expand the dictionary, we translated the SentiWordNet dictionary, which contains more than 117,000 words, into Turkish using Google Translate[1] and we performed the morphological analysis. After that, the polarity score of each word was calculated. We have added the words that are not in the SWNetTR dictionary to the translated dictionary. In this way, 110,648 words were added to the translated dictionary. In its final form, there are 159,876 words in the translated dictionary. Some examples from the translated dictionary are shown in Table 1:

TABLE I. Example Words from Translated Dictionary

Word	*Polarity (Tone) Value*	*Sentiment Polarity*
âbâd etmek *(to worship)*	0.28651	positive
bulutlanmak *(cloud over)*	-0.25000	negative
doğrulanabilir *(verifiable)*	0.70318	positive
zifiri karanlık *(pitch dark)*	-0.12500	negative
eş biçimli *(isomorphic)*	0.12500	positive
yokuş *(ramp)*	-0.16346	negative
maliyet *(cost)*	-0.11041	negative
kilometre *(kilometer)*	0.16151	positive
kümülatif *(cumulative)*	0.16151	positive
ayrılamaz *(inseparable)*	-0.56250	negative

GDELT Dictionary:

While preparing our 'GDELT' dictionary, the content on the website was accessed by using the BeautifulSoup library designed for python. This content was downloaded as zip

[1] https://www.translate.google.com/

files, and the excel files in it were extracted using the python programming language. These operations were carried out by selecting only the news in Turkish.

Since the HTML-tag names and design styles of the content on each news are different, a dynamic solution could not be found to reach the news without corrupting it. Therefore, the content of the websites was carefully selected. The HTML-tag names containing the 'content' part of these websites were manually selected, extracted into excel files with the help of the BeautifulSoup library, and converted into 'Json' format and stored.

Before processing these files, we keep, a further extraction process is carried out by examining whether the content is Turkish or not. Unwanted links, symbols, etc., in the texts are filtered as preprocessing step of the data.

The next step is morphological analysis step: with the help of Zemberek library the words in the texts were tokenized and separated into their roots one by one by applying normalization. At this stage, a multi-words handler module was created using the list containing 18,003 multi-words obtained from the 'multi-word expression script' from Kemal Oflazer et al. [14]. This module was carried out by searching the words in a list from the text, and the polarity scores of the words were calculated with the help of Eq. (1):

$$S_w = x = \frac{\sum_{i=1}^{n}(f_i * d_i)}{\sum_{i=1}^{n}(f_i)} \quad (1)$$

where n shows the total number of documents containing the word, d indicates that the polarity score of the document, f_i represents the number of occurrences of the word in the document and S_w shows the calculated polarity score of the word.

Moreover, in order to strengthen the calculated polarity values, a 'Booster Words' list which has significant words for the corresponding common expressions.

As a result of these processes, new words that were not included in our 'SWNetTR' dictionary were added at every step, and our dictionary reached 84,744 words at the end. Some examples from the GDELT dictionary are shown in Table 2:

TABLE II. EXAMPLE WORDS FROM GDELT DICTIONARY

Word	***Polarity (Tone) Value***	***Sentiment Polarity***
arz *(supply)*	0.05373	positive
başlama *(start)*	0.07849	positive
yoksun *(devoid of)*	-0.32741	negative
kelepçe *(handcuff)*	-0.09672	negative
hususiyet *(specialty)*	0.07641	positive
fark etmek *(to notice)*	0.19134	positive
düzenli *(organised)*	0.11863	positive
cezalandırma *(punishment)*	-0.30540	negative
amino asit *(amino acid)*	0.43141	positive
metrik *(metric)*	-0.33333	negative

B. Our Approaches

Algorithm-1: Semantic polarity itself is the classification criteria of a word whether positive or negative. Tweets' words in the dataset were separated to their roots. The semantic value of each word in each text instance was searched from the dictionary. Each text instance was classified based on the number of positive and negative words. Then, the classification performance of the algorithm was determined based on F1-score the evaluation metric.

Algorithm-2: To calculate the semantic polarity value for each text instance, the frequency of each word in the text instance was calculated. Then, the frequency value and semantic polarity value of each text instance were multiplied. Obtained values were summed. According to the sum value, a suitable label is assigned to the corresponding text instance. The formula for calculating the semantic polarity value is given in Eq. (2):

$$\text{Semantic Polarity} = \sum_{i=1}^{n} word_i\, frequency * word_i semantic\ polarity \quad (2)$$

Algorithm-3: Semantic polarity values were calculated. Each word in the text instance was checked from the booster/seed words list. If the word is in the booster/seed words list, the frequency of the word in the text and four times of semantic polarity value were multiplied. This process was repeated for each word in the text instance and results were summed. The formula for calculating the semantic polarity value is given in Eq. (3):

$$\text{Semantic Polarity} = \sum_{i=1}^{n} word_i semantic\ polarity * \begin{cases} word_i frequency * 4\,, if\ i\ \in booster||seed\ words \\ word_i frequency,\ \ if\ i \notin booster||seed\ words \end{cases} \quad (3)$$

Classification process is performed according to the positive/negative sign of the calculated score. If the calculated semantic value was positive, the text instance was classified as positive, and if it was negative, the text instance was classified as negative.

Algorithm-4: Firstly, a $n \ x \ m$ matrix where m represents the number of data, and n represents the number of words in the text instance was created. The created data was sent to the model which is created with the SVM algorithm.

The general architecture of the system presented in this study is given in Fig 1.

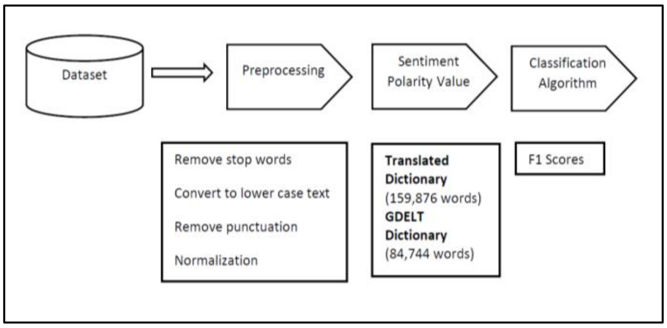

FIGURE I. GENERAL ARCHITECTURE OF THE SYSTEM

IV. EXPERIMENTS AND RESULTS

A. Datasets

In this study, two data sets were used. The properties of the data sets are as given in Table 3 below.

TABLE III. PROPERTIES OF THE DATASETS

Dataset	Content	Dataset Size	Positive Tweet %	Negative Tweet %
Dataset-1	Tweets	4202	63%	37%
Dataset-2	GDELT News Data	12000	36%	64%

The first dataset consists of Tweets. This dataset includes 4,202 tweets, and these tweets in the dataset are classified into two categories, which are positive tweets and negative tweets. 63% of the tweets in this dataset are sentimentally positive and the remaining 37% of the tweets in the dataset are sentimentally negative.

The second dataset consists of GDELT news. This dataset includes 12,000 GDELT news, and this news in the dataset are classified into two categories which are positive sentiment and negative sentiment. 36% of the reviews in the dataset are sentimentally positive and the remaining 64% of the reviews in the dataset are sentimentally negative.

Data in these datasets were predetermined as positive or negative. In all the experiments, the dataset is divided into as 70% training set and 30% test set.

B. Experimental Setup and Environment

Two different data collection stages were carried out in the study. In the first stage, tweets shared by users on the Twitter platform were collected. For this, a diffusion algorithm was developed by accepting some accounts with high follower numbers as root, and tweets in Turkish were collected from thousands of different users without any limitation. Collected Twitter data was stored on our local server by indexing on MongoDB. We apply 3-fold-cross validation and report the average of the experimental results.

Turkish news texts were collected in the second stage through the 'GDELT' Project, the largest and most comprehensive open database ever created. The reason for collecting data over 'GDELT' is that news is already labeled. At this stage, zip files downloaded from GDELT were extracted one by one, and news sites in Turkish were extracted. Then, Turkish news sites were examined one by one by human experts, and it was determined which HTML tag and which class/id name the news was in. After this stage, the content of the news was collected one by one with the python code and stored in JSON files.

C. Baseline Algorithms

In this study we used 3 state-of-the art algorithms for baseline algorithms. The first baseline algorithm is the SVM algorithm with linear kernel. The second baseline algorithm is NB algorithm which is based on Bayes theorem. The third and final baseline algorithm is Random Forest (RF) classification algorithm

D. Evaluation Results and Discussions

Experimental results are shown in Table 4 and Table 5. The experimental results of the suggested algorithms and the baseline algorithms on Twitter 4K dataset are shown on Table 4. According to the experimental results, all of the suggested algorithms are superior to all of the baseline algorithms in this dataset. For example, with GDELT Dictionary, the F1 scores of ALG1, ALG2, ALG3 and ALG4 are 75.34%, 76.81%, 80.12% and 82.46% whereas the F1 scores of SVM, NB and RF are 74.11%, 68.13% and 71.39%; respectively. Furthermore, with Translated Dictionary, the F1 scores of ALG1, ALG2, ALG3 and ALG4 are 73.64%, 74.77%, 79.88% and 80.17%; respectively. These experiment results show that both sentiment polarity dictionaries improve the classification performance on Twitter 4K Dataset for Turkish sentiment polarity detection task.

Semantic Polarity Dictionary	*ALG 1*	*ALG 2*	*ALG 3*	*ALG 4*	*SVM*	*NB*	*RF*
GDELT	75.34	76.81	80.12	82.46	74.11	68.13	71.39
Translated	73.64	74.77	79.88	80.17			

TABLE IV. F1 SCORES (%) OF THE SUGGESTED ALGORITHMS AND BASELINE ALGORITHMS ON TWITTER 4K DATASET

The experimental results of the suggested algorithms and the baseline algorithms on GDELT News 12K dataset are shown on Table 5. According to the experimental results, all of the suggested algorithms are superior to all of the baseline algorithms in this dataset. For example, with GDELT Dictionary, the F1 scores of ALG1, ALG2, ALG3 and ALG4 are

79.48%, 81.37%, 84.20% and 86.73% whereas the F1 scores of SVM, NB and RF are 80.61%, 74.32% and 77.39%; respectively. Furthermore, with Translated Dictionary, the F1 scores of ALG1, ALG2, ALG3 and ALG4 are 77.09%, 79.11%, 81.19% and 84.36%; respectively. These experiment results show that both sentiment polarity dictionaries improve the classification performance on GDELT News 12K Dataset for Turkish sentiment polarity detection task.

TABLE V. F1 SCORES (%) OF THE SUGGESTED ALGORITHMS AND BASELINE

<table>
<tr><th>Semantic Polarity Dictionary</th><th>ALG1</th><th>ALG2</th><th>ALG 3</th><th>ALG 4</th><th>SVM</th><th>NB</th><th>RF</th></tr>
<tr><td>GDELT</td><td>79.48</td><td>81.37</td><td>84.20</td><td>86.73</td><td rowspan="2">80.61</td><td rowspan="2">74.32</td><td rowspan="2">77.39</td></tr>
<tr><td>Translated</td><td>77.09</td><td>79.11</td><td>81.19</td><td>84.36</td></tr>
</table>

ALGORITHMS ON GDELT NEWS 12K DATASET

The superiority of the offered algorithms could be explained with the contribution of sentiment polarity values in both dictionaries and also the usage of booster/seed words list. GDELT sentiment polarity dictionary was built by expanding the capacity of existing SwNetTR++ dictionary to 84,744 words. Furthermore, we also built a translated sentiment polarity dictionary for Turkish which contains 159,876 words. Both these sentiment dictionaries can be accessible for the researchers upon their request.

V. CONCLUSIONS AND FUTURE DIRECTIONS

In this study we developed a series of statistical-based semantic algorithms for Turkish SA problem. Moreover, we conducted experiments on SA in Turkish texts using different sentiment polarity dictionaries: We built the first sentiment polarity dictionary by using a translator and this dictionary includes about 159,876 terms. We built the second sentiment polarity dictionary by using GDELT platform and this dictionary includes about 84,744 terms. We conduct our experiments on two datasets and compare the classification results of the suggested algorithms with the classification results of baseline algorithms. The experiment results show that the offered algorithms with their included sentiment polarity dictionaries are very valuable for Turkish sentiment polarity detection task. There are three important conclusions of this study: 1.) We built two publicly available sentiment polarity dictionaries for Turkish, 2.) We developed statistical-based novel semantic algorithms in order to handle Turkish SA problem, 3.) We report the observations of the effect of using different semantic-polarity dictionaries on Turkish sentiment polarity detection task.

As a future work, we want to extend our sentiment polarity dictionary into 200,000 words-capacity. We will also conduct a negation handler and ambiguity resolver modules into our sentiment polarity detection algorithms. An additional item in our agenda is to expand our approaches by adding further semantic-information and investigate how the construction of these sentiment values can affect the performance.

ACKNOWLEDGEMENTS

This work was supported in part by the Scientific and Technological Research Council of Turkey (TÜBİTAK) with grant number 120E187. Points of view in this document are those of the authors and do not necessarily represent the official position or policies of TÜBİTAK.

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