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Language Independent Word Polarity Detection using Star Rating

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***Abstract*—The continuous and rapid evolution of the Internet along with increased accessibility to social media platforms has led to an exponential growth in the amount of content posted online by users daily. Sentiment Analysis (SA), a field of Natural Language Processing (NLP), is nowadays necessitated to be performed on user-generated content in order to extract valuable information. This paper proposes a methodology to determine the polarity of a word based on its occurrence in positive / negative product reviews. The star rating of a review is used to classify it as positive or negative. The proposed methodology has been implemented using a German language Amazon product review dataset, although the algorithm is independent of any language. F1-score thus obtained is 72% which is better than the lexicon-based baseline sentiment analysis for German language.**

***Index Terms*— Sentiment analysis, Lexicon, Reviews, German language, Polarity.**

I. Introduction

With the expansion of e-commerce and social media platforms, the expression of opinion by users on the Internet on a wide range of issues has increased manifold. From writing blogs to tweets to product reviews, the engagement of users on social media platforms is high. Such opinion-oriented data on the Internet calls for Sentiment Analysis (SA), or opinion mining. SA of online product reviews helps organizations to gain insights on how consumers perceive their products.

Several studies dedicated to sentiment analysis of text in the English language can be found in the literature [1]–[7]. But the development of SA in other native languages like German, Chinese, Hindi, Urdu, Spanish, Arabic etc. has also gained momentum recently [8]–[13].

There are mainly two methods to perform sentiment analysis of text: lexicon-based (also called rule-based/dictionary-based) methods and machine-learning (ML) based methods [2], [14], [15]. The first approach incorporates the usage of a lexicon containing a list of sentiment bearing words (SBWs) along with their sentiment orientation [14], [15]. The second approach involves training the machine learning (ML) classifier with training data and predicting the sentiment of test data using the trained model [16].

This paper demonstrates a lexicon-based approach to perform sentiment analysis of online product reviews in the German language. The authors have an intermediate level knowledge of German without being natives which

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makes the task even more challenging and interesting.
Although ML-based methods generally achieve a higher performance than rule-based methods, their requirement for large, annotated corpora limits their usage for a non-English language [14]. Hence, it only makes sense to improve upon the performance of lexicon-based approaches as they do not require any training data and are easy to comprehend as well [17]–[20].
It is observed, when an unknown word is encountered while reading a piece of text, its meaning can be inferred from the context of the text, without looking up that word in a dictionary. Thus, the main intuition behind this work is that the sentiment orientation of a word can be calculated based on its occurrences in product reviews. If the word appears in more positive reviews than negative ones, then it is more likely that the word is positive. Similarly, if the word appears in more negative reviews, then the probability of the word being negative is higher.
The decision to classify a review as positive or negative is based on its star rating. The review body could have a sarcastic undertone reflecting it to be positive, which is a misinterpretation. On the other hand, the star rating given by a customer is generally a direct reflection of his/her perception of the product [21] and could be considered a more reliable source of opinion expression [22].
The key contribution of this research paper is the detection of the polarity of an opinion word as positive or negative depending on the type of reviews it is appearing in, which is a simple approach yet comes out to be effective as observed experimentally. The application of this method is to detect the polarity of any given word thereby enhancing any standard lexicon by adding more words with their polarities in it. For the implementation of this study, German language has been selected, however, the technique can be extended to any language as polarity computation is only dependent on the review rating and not on the review text.
The rest of the paper is organized as follows. Section II focuses on the pertinent literature surrounding rule-based sentiment analysis and the applications of star ratings in reviews. Section III discusses the corpus and the lexicon employed in this study. Section IV presents the methodology proposed to achieve the objective. Section V covers the experiments conducted and the results hence obtained. Section VI concludes the paper along with future work.

II. RELATED WORK

Product reviews serve as a major factor in decision-making by customers purchasing a variety of products online [23], [24]. Various studies indicate that online shopping behavior of a customer is predominantly influenced by the reviews given by other customers [25], [26]. Not just product reviews, but movie reviews, book reviews and various other kinds of feedback provide valuable information to potential users. Thus, extracting opinions from reviews makes for a significant study.
Several studies have been conducted across multiple languages using both rule-based as well as ML-based approaches to sentiment analysis of online product reviews.
In [15], the author has constructed an education sentiment lexicon to classify student feedback in English with the objective of enabling educators to assess the effectiveness of teaching practices. Without using the constructed education sentiment lexicon, the accuracy achieved was 77.65% which increased to 86.45% with the usage of the education sentiment lexicon. The lexicon, however, is restricted to the domain of education, containing words more likely to appear in student feedback.
The authors of [27] extended their previous works [28], [29] on construction of PerSent, a Persian sentiment lexicon to analyze Persian reviews belonging to news, product and movie domains. The recent extension additionally allows for the detection of 1000 idiomatic expressions manually coded into the lexicon. This does not allow for the automatic detection of new slangs and idiomatic expressions.
A multi-domain sentiment dictionary was built in [30] to classify target domain reviews as positive or negative in the Hindi language. The creation of the dictionary is achieved by calculating Pointwise Mutual Information (PMI) and relatedness weight. This dictionary is then employed in classifying target reviews. The approach achieved an accuracy of 76%. The work has been specifically developed for the Hindi language and is not a language agnostic algorithm.
The authors in [31] developed a German adaptation (GerVADER) of the English sentiment lexicon VADER [32]. The F1-measure obtained after applying the created lexicon on corpora spanning over multiple domains like news and sports, is between 39%-74%. The lexicon performs poorly as compared to its well-established counterpart VADER due to the inability to detect negations, German-specific phrases and slangs.

In [8], the authors have utilized different transformer-based models like BERT, ELECTRA, RoBERTa, and XLM RoBERTa for relevance and polarity classification of German customer feedback dataset, achieving an accuracy score of 85.3%. Such an approach requires pre-trained models.

The authors in [33] performed sentiment analysis of the Urdu language using machine learning and deep learning algorithms. It was concluded that deep learning based models performed better than ML-based models.

The focus of this paper is to devise a very simple yet effective approach for polarity classification of a word. The method only utilizes the review ratings given by customers in order to achieve the objective making it language independent. Although ML-based and deep learning based approaches outperform lexicon-based approaches, they are not as comprehensible and transparent as lexicon based techniques [34]. Thus, it is imperative to work further upon lexicon-based approaches.

III. Resources

A. Reviews' Corpus

The reviews' corpus employed in this study consists of a total of 10,000 reviews written in the German language about the products available on Amazon. These were collected between November 1, 2015 and November 1, 2019 [35]. Each review consists of a review ID, review title, review body, reviewer ID, star rating, product ID and product category. The star rating ranges on an ordinal scale of an ordered set of numerical values (one to five stars). Fig. 1 shows a sample review in German from the reviews' corpus.


```
  "review_id": "de_0591095",
  "product_id": "product_de_0301773",
  "reviewer_id": "reviewer_de_0787123",
  "stars": "1",
  "review_body": "Das Produkt kam bis heute nicht bei mir an. Ich bin stocksauer! Trotz der
langen Lieferzeit (sollte zwischen dem 1. und 10. März geliefert werde), ist das Produkt auch
eine Woche nach dem spätesten Lieferdatum nicht angekommen.",
  "review_title": "Produkte NICHT geliefert",
  "language": "de",
  "product_category": "toy"
```


Figure 1. A sample review in German language from the reviews' corpus

B. Lexicon

The lexicon used in this study is the SentimentWortschatz (*SentiWS)*, a publicly available German-language resource for sentiment analysis [36]. It has two separate lists of positive and negative sentiment bearing words along with their polarity scores lying in the interval [-1, 1], their part-of-speech (POS) tag and their inflections. The version of SentiWS used in this work is v2.0. Fig. 2 shows a sample entry in the *SentiWS.*

Word	**POS Tag**	**Weight**	**Inflections**
Einkauf	NN	+0.0040	Einkäufen,Einkäufe,Einkaufes,Einkaufs,Einkaufe

Figure 2. A sample entry in SentiWS

IV. Proposed Methodology

A. Preprocessing of Reviews' Corpus and Lexicon

In the preprocessing of the reviews' corpus ***R***, the following steps were taken -

1. Removal of any HTML tags, digits, non-ASCII characters, non-European characters, non-whitespaces, single letter words, and stop words.
2. Keeping only words with part-of-speech (POS) tag as ADJ (adjective), ADV (adverb), NOUN (noun), PART (particle), VERB (verb) since only such words are considered to bear opinion.
3. Lemmatization of all the words obtained in step 2. Let this lemmatized list of words be ***L***.

In the preprocessing of the SentiWS lexicon ***S***, the following steps were taken -

1. Lemmatization of all the words in the positive and negative lists of the lexicon.
2. Dropping duplicate lemmatized words from both positive and negative lists.

After the pre-processing of review corpus and the lexicon, the following step is performed -

Searching every word of ***L*** in the positive and negative lists of ***S*** -

- If the word is found, it is inserted in L_{pos} or L_{neg} (empty initially) respectively along with its polarity score.
- If the word is not found in either of the lists, it is inserted in $L_{indeterminate}$.

B. Word Polarity Detection using Review Star Rating

Let R represent the reviews' corpus.
Let L_{test} be the union of L_{pos} and L_{neg} i.e. $L_{test} = L_{pos} \cup L_{neg}$
The aim is to detect the polarity of every word, say ***testWord***, in L_{test} using customer review ratings in R. Reviews with ratings of 1 or 2 are considered as negative and the reviews with ratings of 3, 4 or 5 are considered positive.
To compute the polarity of a ***testWord***, the following steps are taken -

1. Find all the reviews in which the ***testWord*** exists in R. Let this subset of reviews be Z i.e., $Z \subseteq R$.
2. If the number of positive reviews in which the ***testWord*** exists is greater than the number of negative reviews, ***testWord*** is classified as positive.
3. If the number of negative reviews in which the ***testWord*** exists is greater than the number of positive reviews, ***testWord*** is classified as negative.
4. If the number of positive reviews in which the ***testWord*** exists is equal to the number of negative reviews, ***testWord*** is classified as neutral.

Fig. 3 illustrates the above stated steps.

V. Experiments and Results

The proposed methodology of word polarity detection is evaluated experimentally, and the results are presented in the table and figures in this section.
Table I shows a sample of test words with their actual polarities in *SentiWS* lexicon along with their calculated polarities using the proposed methodology. The fourth and fifth columns in the table depict the count of positive and negative reviews respectively in which the ***testWord*** occurs. The sixth column indicates whether the calculated polarity of the test word matches its actual polarity as per *SentiWS* lexicon or not.
Fig. 4 depicts the confusion matrix where TP = true positive, FP = false positive, FN = false negative and TN = true negative.

TABLE I. ACTUAL POLARITY OF TEST WORDS IN SENTIWS VS POLARITY OBTAINED USING PROPOSED METHODLOGY

Test Word	**Polarity in SentiWS lexicon**	**Polarity using proposed methodology**	**Positive Review Count**	**Negative Review Count**	**Match or mismatch?**
gut (good)	0.004	Positive	1995	705	Match
schön (beautiful)	0.0081	Positive	509	182	Match
Qualität (quality)	0.004	Positive	419	271	Match
funktionieren (to function)	0.004	Positive	307	282	Match
lösen (to solve)	0.004	Negative	84	115	Mismatch
komplett (complete)	0.004	Negative	36	89	Mismatch
knapp (scarce)	-0.2036	Negative	41	45	Match
beschädigen (to damage)	-0.335	Negative	31	57	Match
Ärger (anger)	-0.3465	Negative	6	11	Match
abbrechen (to break)	-0.3482	Negative	25	45	Match
schwierig (difficult)	-0.0245	Positive	30	17	Mismatch
Nachteil (disadvantage)	-0.8102	Positive	26	7	Mismatch

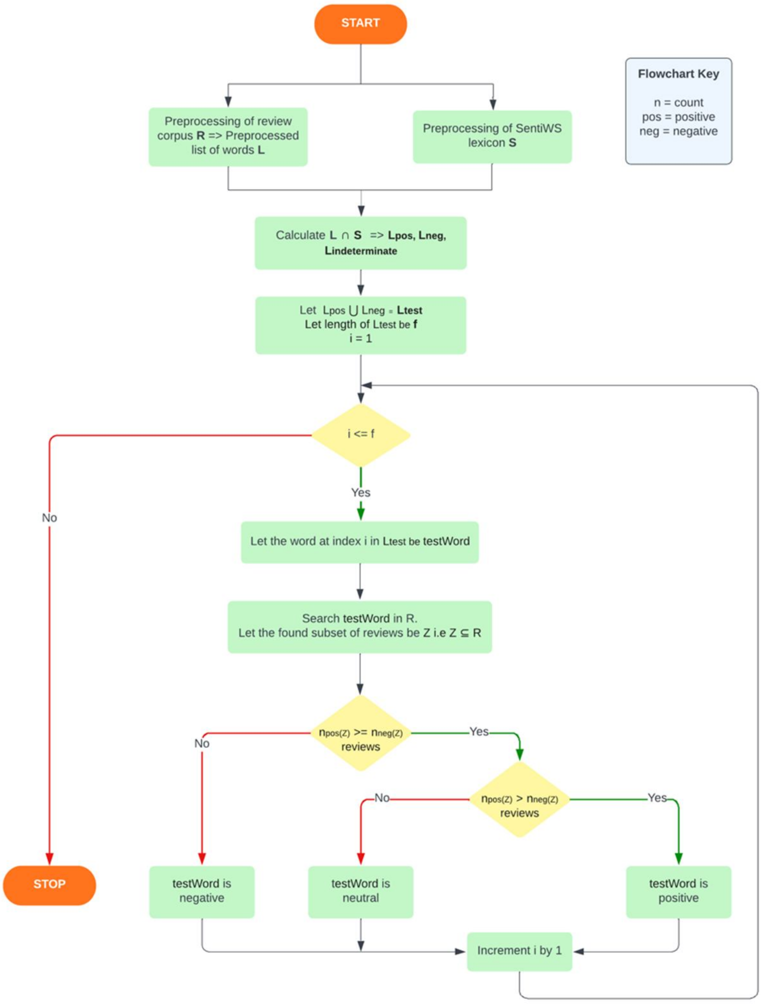

Figure 3. Proposed methodology

		Actual Values (*Positive*)	Actual Values (*Negative*)
Predicted Values	(*Positive*)	TP = 517	FP = 240
	(*Negative*)	FN = 153	TN = 301

Figure 4. Confusion matrix

Fig. 5 and Fig. 6 represent the percentage distribution of positive and negative words detected by the proposed algorithm.

The proposed methodology of word polarity calculation is also evaluated using F-score metric. It combines both 'Recall' and 'Precision' and is a more balanced metric [5] as given in (1).

$$F\text{-}score = 2 * \left(\frac{Precision * Recall}{Precision + Recall}\right) \qquad (1)$$

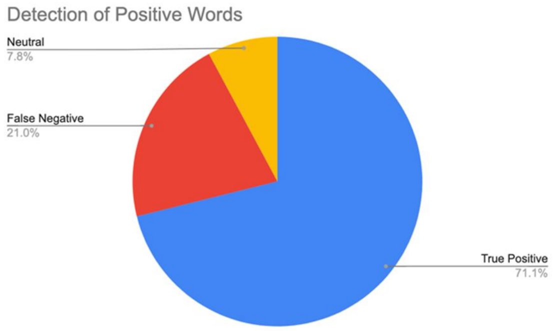

Figure 5. Percentage distribution of detected positive, negative and neutral words during positive words classification

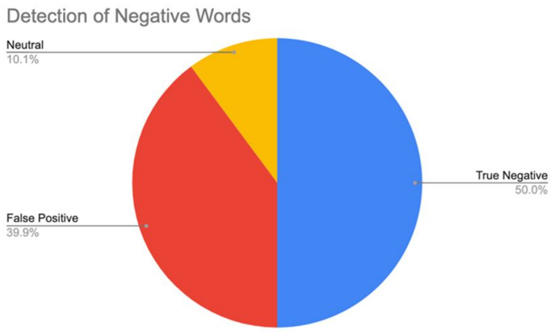

Figure 6. Percentage distribution of detected positive, negative and neutral words during negative words classification

The experimental results on the dataset, Amazon product reviews using the proposed methodology gave an F-score of 72%, which is a significant improvement over 67% F-score [14] achieved in various studies on rule-based SA in German. The proposed approach is simple yet accurate, incorporating only star ratings. Furthermore, the polarities of the words in the list $L_{indeterminate}$ (whose polarities were not present in *SentiWS* lexicon) can also be computed using the suggested algorithm.

While classifying positive words, the algorithm can correctly classify 71% of the words, whereas while classifying negative words, the algorithm correctly classifies only 50% of the words. The prime reason behind this is that the algorithm does not consider negation words. Thus, further improvisation in classifying a word correctly is under consideration.

VI. Conclusion and Future Work

Sentiment analysis is a fairly evolving field. Since lexicon-based methods for performing sentiment analysis are more comprehensible, the idea of associating polarity to any given word allows for the generation of new as well extension of standard language lexicons.

This study addressed the problem of identifying the polarity of a given word by looking for its occurrences in online product reviews and considering whether it occurs more in positively rated or in negatively rated reviews. By comparing the calculated polarities of words in the review corpus with their known polarities (as per SentiWS lexicon), the F-score so obtained is 72%. The suggested approach allows for the application of the algorithm on the corpus of any language, making the algorithm language independent and can further be successfully applied to enhance any standard lexicon by adding new words with their polarities in it.

In future, apart from detecting the polarity of a word (positive, negative or neutral), the algorithm will be extended to calculate the sentiment score of the word as well. Moreover, the proposed methodology will also be evaluated on various national languages like Hindi, Bengali, Marathi and international languages like French, Spanish and Persian.

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