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SENTIMENT ANALYSIS USING THE VADER MODEL FOR ASSESSING COMPANY SERVICES BASED ON POSTS ON SOCIAL MEDIA

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ABSTRACT

The provision of services by companies in specific domains requires continuous commitment and a constructive approach to meet customer requirements, however, it is often challenging to determine the level of customer satisfaction without their feedback. Therefore, this paper attempts to provide a solution to this problem by using comments from social networks and evaluating their sentiment using the VADER model.

In order to accomplish the aim of our research, a lexicon has been built with more than 9500 adjectives and verbs from the Albanian language based on VADER which is just in the initial form and the sentiments are evaluated as positive, neutral, or negative. The lexicon was constructed for the Albanian language and two companies of the Republic of Kosovo were researched as case studies.

Furthermore, the sentiment estimation, using the VADER model, in case of our datasets, we obtained a high accuracy, approximately between 89% and 95%. This level of accuracy has been primarily attributed to the application of all preprocessing steps within the dataset, which significantly enhances the model's performance.

Key words: Sentiment, Vader model, social network, posts, sentiment evaluation

INTRODUCTION

The analysis is conducted on entities such are services, issues, individuals, products, events, objects, organizations, and their respective attributes. In this context, every customer's opinion concerning these entities, particularly regarding the company's services, holds value and should be assessed for a potential improvement or even complete change depending on the outcomes generated by the evaluation process.

It is crucial for the company to employ the most up-to-date and suitable methods to identify gaps or weaknesses that may exist within the organization, in order to enhance its performance. As a result, this requires a more accurate finding of groups as well as an accurate evaluation of the opinion based on the comments within the group. To achieve the above-mentioned solution, the choice of the most appropriate methods of clustering and sentiment analysis is crucial, and in some cases not an easy task, especially when we do it for a low - resources language such as the Albanian language. Hence, as already mentioned, this research is conducted for the Albanian language and the comments written in this language.

Also, the application of similar algorithms is notable example worth mentioning in utilization of the BERT transformer model (Bidirectional Encoder Representations from Transformers) in conjunction with supervised algorithms such as CNN (Convolutional Neural Network), RNN (Recurrent Neural Network), and BiLSTM (Bidirectional Long Short-Term Memory), and this form of using these models corresponds to the model we have chosen. Accordingly, combination models mentioned before demonstrating excellent performance and effectiveness in various tasks within natural language processing are applicable in other cases as well (Bello, A. Ng, S.C. Leung, M.F, 2023). In instances where clustering results through unsupervised algorithms are involved, the VADER (Valence Aware Dictionary and Sentiment Reasoner) model is widely employed since it proves to be a suitable method for sentiment analysis in such cases (Hutto, C.J. & Gilbert, E.E, 2014).

The VADER sentiment analysis tool combines a lexicon-based and rule-based approach to analyze text and assign it as a positive, negative, or neutral sentiment. Additionally, this generates a compound score that considers all three sentiments. This tool is particularly effective in analyzing social media content due to its ability to manage emojis, acronyms, slang, and contractions commonly found in such texts.

Besides, this paper also introduces the model for sentiment analysis in the Albanian language, using the lexicon developed for the experiments and analysis conducted in this

research. The lexicon is currently in its initial stages and provides an opportunity for further advancement and development by others.

The paper is structured as follows: part II presents the methodology employed during this research, whereas part III discusses the contributions made in this field up to this point. Next, part IV presents the results, and then the paper concludes in the final section, part V, by summarizing the conclusions and addressing the challenges faced in this research.

THE METHODOLOGY USED IN OUR RESEARCH

Sentiment analysis is a text analysis approach that categorizes texts data into three distinct categories: positive, neutral, and negative (MF, 2018). Consequently, the preparation and adaptation of the data requires a special and careful approach, particularly in modifying the lexicon to be employed and subsequently feeding the VADER model with the targeted dataset.

The datasets are taken from official fan pages of two companies on social media such as Vala Telecommunication (this will be written as X dataset) and Art Motion (which will be written as Y dataset).

Similar examples of VADER model application we found out in research of (Hutto, C.J. & Gilbert, E.E, 2014), they have created a lexicon of the English language containing 7520 different terms, and it was the fundaments in creation of our lexicon. The model used in this paper includes a comprehensive constructed list of adjectives and verbs, both unigram and bigram, and to each assigned specific weights. These values mean the evaluation of individual words which are categorized into positive, neutral or negative intervals.

In this respect, consultation with a linguistic expert was necessary to correctly determine the weight of each word in the construction of the sentence. Initially, after assessing and reviewing each term in the constructed lexicon, in order to ensure more optimal performances in sentiment assessment we went further and took some additional steps as well operations and improvement. The steps include:

- *Checking for duplicate terms;*
- *Removing meaningless words (in the Albanian language);*
- *Removing words that are not in the Albanian language;*
- *The use of unigrams and bigrams;*
- *Verbs in different tenses, for example: (alb: kalon, kaloj, kalova, kalove, etc;).*
- *Adding special letters of the Albanian language such as ë, ç, etc.;*

- *Setting the weight for each term, checking the intensity/value that a certain term has, and checking the connections with other words of that term, etc.*

Using the idea of creation and the form of application the lexicon created by authors (Hutto, C.J. & Gilbert, E.E, 2014) in their research, we created a lexicon that consists of 9568 construction of sentences, which define the feeling's weight and using those we find out the feeling of each comment, either positive, negative, or neutral..

It is worth mentioning that the built lexicon, in the future, can be supplemented with other data to improve the evaluation values and increase the sentiment assessing accuracy. However, based on the obtained results in our research with our two datasets, we consider that the model performs quite well for this phase and with the mentioned number of terms. Evaluation of comments is done by taking into account several conditions in the collective evaluation (composite score) to accurately classify each comment as positive, neutral or negative. The composite score is obtained by summing the valence scores of each word in the lexicon, including adjustments based on predefined rules, and normalizing the score to a range between -1 (extremely negative) and +1 (extremely positive).

In the classification process, we use the following rule to determine the sentiment (positive, negative, or neutral) of each comment:

- **Positive sentiment**: compound score >= 0.05;
- **Neutral sentiment**: (compound score > -0.05) and (compound score < 0.05);
- **Negative sentiment**: compound score <= -0.05.

It is worth mentioning that during our experiments, we observed that when the preprocessing stages are applied, the model achieves higher accuracy. This is attributed to the fact that the model employs a lexicon based on uni- and bi-gram words, which evaluates each word within a sentence. Consequently, this approach results in more accurate sentence-level sentiment analysis.

LITERATURE REVIEW

In general, the process of evaluating different opinions relating to a single or multiple cases requires a specialized and precise approach to ensure a comprehensive understanding of each opinion or comment. As a result, different models are used for this purpose and their accuracy varies depending on the attributes and parameters considered as the basis.

In this context, several models have been used, with continuous improvements to identify the most optimal application. Some of these models include: *BERT* (J. Devlin, M.-W.

Chang, K. Lee, and K. Toutanova, 2019), (Bello, A. Ng, S.C. Leung, M.F, 2023), *VADER model* (Hutto, C.J. & Gilbert, E.E, 2014), Log Term Frequency-based Modified Inverse Class Frequency (LTF-MICF) model (Parveen et al., 2023), MaxDiffTwitter (Kiritchenko S, Zhu X, Mohammad SM, 2014), HuandLiu (with 6786 words) (Hu M, Liu B, 2004), SenticNet (Cambria E. Olsher D. & Rajagopal D., 2014), and SentiWordNet (Baccianella S, Esuli A, Sebastiani F., 2010).

The VADER model is widely used across various domains and languages for sentiment analysis. In the sentiment analysis process, the model generates a numerical score that signifies the intensity or strength of the sentiment expressed in the input text. The score generated by the VADER model is represented by a positive or negative number. A positive score indicates a positive sentiment expressed in the text, while a negative score suggests a negative sentiment.

The VADER was firstly implemented for contents in English language, and then it was extended and implemented for other languages as well, including German. This adaptation involves adjusting and customizing the model to effectively analyze sentiment in German-language content (K. M. Tymann et al., 2019). In their research, authors utilized multiple corpora containing substantial amounts of data across various content types, namely SB10K, Scare, and News App. The evaluation of the VADER model's performance on these corpora yielded average accuracy rates of 71.3% for the News App corpus, 72% for SportNews, and approximately 52% for SB10K.

These results demonstrate the suitability of the model, nevertheless, the authors emphasize the crucial significance of lexicon adaptation in achieving the highest attainable accuracy. Furthermore, (A. Amin, I. Hossain, A. Akther and K. M. Alam, 2019), employed and customized a model to analyze Bengali language text. Their research focused on adapting the model to effectively manage sentiment analysis tasks in the Bengali language. To adapt and enhance its support for the Bengali lexicon, this model incorporates various techniques such as bigrams, trigrams, and negations, along with the other preprocessing stages. Moreover, it modified the model to successfully process and analyze Bengali language text without relying on translation tools like GTranslate or MyMemory Translator. The corpus utilized in their research is SentiWordNet, which they translated into Bengali.

Indeed, the VADER model has proven its versatility by extending beyond linguistic contexts and demonstrating successful performance in various projects involving diverse content types. One such instance is presented by (Sally, 2022), where three distinct models launched in 2021 were considered: Apple iPhone 13, Google Pixel 6, and Samsung Galaxy S21. The findings of this paper reveal that positive comments have been detected by the

VADER model, where comments were initially analyzed using several supervised algorithms, including Naïve Bayes, Decision Tree, and Support Vector Machine (SVM). Among the algorithms employed, SVM achieved the highest average accuracy of 76% across the three methods, followed by Naïve Bayes with 75.3%, and Decision Tree with 70%. The authors also evaluated the performance of each service using standard metrics such as Precision, Recall, and F1-score, presenting the results in separate tables.

The VADER and NLTK models were utilized in a study conducted by (Shihab Elbagir and Jing Yang, 2019), which focused on analyzing Twitter data related to the 2016 US presidential elections. The authors explored the application of these models to gain insights from the collected Twitter data. The main reasons why these two models have been used are to avoid the evaluation of polarity in binary form, and to evaluate it in multi-classification form. One notable advantage of using the Vader and NLTK models, as perceived by the authors, is that they do not require pre-training of the data. Also, they can be readily applied on the data without the need for extensive prior training. Additionally, these models exhibit the capability to efficiently process large volumes of data, enabling the generation of results swiftly. The efficiency of these models in terms of time and application is indeed notable. The authors have reported accuracy percentages for different polarity classes, with highly positive at 2.4%, positive at 26.5%, neutral at 46%, negative at 22.8%, and highly negative at 1.48%. These results demonstrate good accuracy in detecting and classifying sentiment across multiple classes, as observed by the authors.

In addition, authors (Mohammed Elsaid Moussa et al., 2018), propose a domain-independent, extendable, and generic lexicon-based framework for sentiment analysis (SA) that utilizes existing tools and techniques. The authors evaluate the framework on four datasets comprising 52,039 reviews using five lexicons. They demonstrated that the framework outperforms each individual lexicon. The authors introduced a neutral bias module to address situations where the sentiment engine fails to determine sentiment due to insufficient information or conflicting scores from different lexicons. They also propose a method to determine the influence of each lexicon on the overall accuracy for a specific dataset and preprocessing method by considering a set of other lexicons as well. The accuracies of different lexicons vary depending on the utilized corpus data. Using the Lemmatization_StopWordsRemoval_AdjX2 methods, the MaxDiffTwitter lexicon achieves an accuracy of 83.01%, the HuAndLiu lexicon achieves an accuracy of 92.20%, and the VADER lexicon achieves an accuracy of 81.36%. The ProsCons dataset shows improved

performance when the StopWordsRemoval method is applied, resulting in an accuracy increase from 80% to 81.60% and an F1-Score of 84.23%.

APPLYING VADER LEXICON RULE BASED

The various methods of classifying messages, comments, and other forms of discussions add to the significance of this automated process, highlighting its importance in analyzing and categorizing textual data. In order to ensure the correct and accurate application of this process, it is essential to evaluate different models that are appropriate for specific cases, topics, or even general scenarios.

This model was chosen due to its suitability for many parameters within the framework of this research. In this case, the VADER model is suggested for the evaluation of polarity in multiple forms, including positive, negative, and neutral, using rules based on the lexicon. This approach deviates from the binary application of polarity evaluation. The aforementioned model utilizes rules or a lexicon containing numerous unigram and bigram terms. These rules or terms play a crucial role in the sentiment analysis process. All of these terms in the lexicon include information about their polarity, intensity (such as highly positive, positive, neutral, negative, and highly negative), and associated values that are generated based on proximity or similarity to the evaluated words.

Furthermore, in our particular case, the chosen model is well-suited as it incorporates a specific list of emotions that has been thoroughly examined and verified with the assistance of a language expert. This ensures the accurate identification of verbs and adjectives within the sentiment analysis process.

DATASETS

Our model has been implemented on a dataset obtained from official social networks of two companies that provide internet and mobile services. The dataset consists of users' comments that are not written in a standardized writing style in the Albanian language. Each comment is dependent on the individual user's writing skills, which posed a significant challenge in expanding the lexicon list to accurately identify and assign specific weights to each term in the sentence.

APPLICATION OF MODEL AND RESULT DISCUSSIONS

The proposed model implementation by using lexicon built in low resource language follows a logical approach which entails utilizing the necessary libraries for implementation. It begins by cleaning and defining the input dataset and subsequently utilizes the lexicon (i.e., the list of terms) to evaluate each sentence within the provided CSV file (corpus).

So, the following pseudocode outlines the sequential steps involved in implementing the model using the Python programming language:

1. *Import relevant libraries*
2. *Create an instance of SentimentIntensityAnalyzer called "analyzer";*
3. *Read a CSV file using relevant library as DataFrame;*
4. *Try:*

   Apply the polarity scores from the lexicon to each row in dataset using the specific function and assign the results to print a new column called polarity;
5. *Then:*

   Sort "data" by the compound VADER score in descending order using the specific function and assign the sorted in DataFrame back to csv file;
6. *Write all results to a new CSV file on the disk using the to_csv method and specifying the file path, index=False, and encoding='utf-8'*
7. *End;*

In Figure 1, a flowchart of the guide is shown illustrating the following steps for applying sentiment assessment using the VADER model.

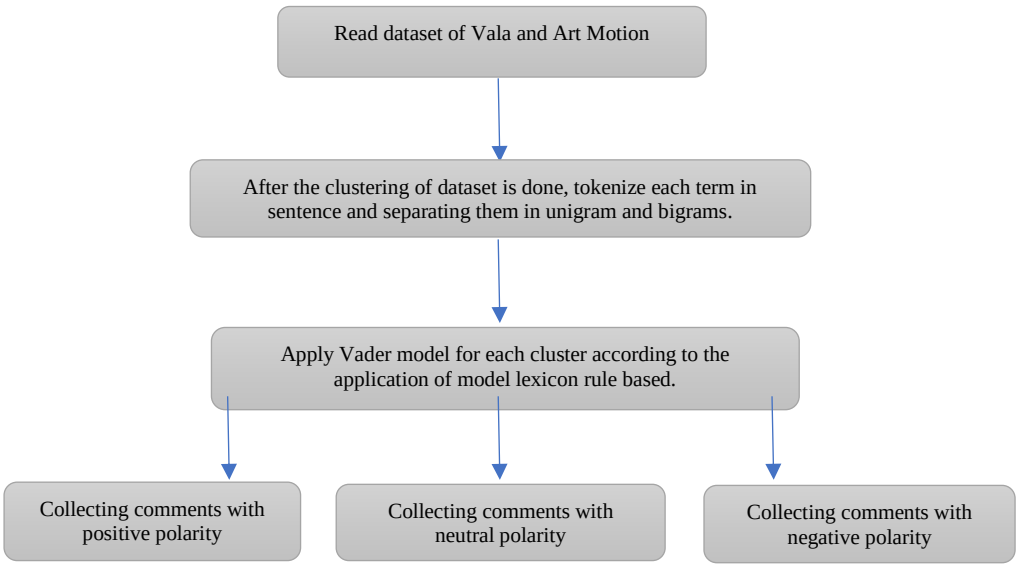


Figure 1: Flow chart of application of evaluation sentiment analysis using Vader lexicon rule based.

The comments provided in Table 1 written in Albanian as illustrative examples are taken from dataset X. These comments are presented in their original form, exactly as users posted them.

Table 1: Evaluation of comments using VADER model with a lexicon in Albanian language.

No.	Comment	Evaluation model	Intensity of comment
1	*Kompania me e mir ne kosov, bravo vala sherbime super te mira"*	*{'neg': 0.125, 'neu': 0.258, 'pos': 0.616}*	*the comment is positive, and intensity is 0.736*
2	*Minutat dhe sms a jon veq brenda rrjetit te vales?* *A edhe ipko e zmobile?*	*{'neg': 0.0, 'neu': 0.674, 'pos': 0.326}*	*the comment is neutral, and intensity is, 'compound': 0.7425*
3	*Po na vjedhni po na sosni saher po i ndrroni ofertat, na knaqtme krejt keto gjana qka po na bani neve, cmime te nalta a knej sherbime jo bash tmira*	*{'neg': 0.752, 'neu': 0.188, 'pos': 0.06}*	*the comment is negative, and intensity is 0.7777*

In this form, the model used with the above-mentioned parameters was applied to both datasets.

As observed in Table 2, two forms of sentiment evaluation are presented. They are divided into two groups: one where the evaluations are accurate and correctly identified, and the other where the model did not perform well in its evaluations. For instance, after manual inspection, we observed that the model occasionally misclassified comments with positive sentiment as negative or neutral, indicating that it failed to correctly assess these sentences or comments. Consequently, we have categorized these evaluations into two distinct groups: "Accurate Evaluation" and "Wrong Evaluation". So, the accuracy of sentiment identification for the X dataset reaches 95.62%. Only a small percentage, 4.38% of the total dataset, was not correctly classified by the model. This indicates that the lexicon built and adapted to the Albanian language is highly effective in capturing the content of the dataset. The fact that only a few comments are not precisely classified in terms of their sentiment suggests that the lexicon adaptation is well-suited to the majority of the dataset's content.

To validate these results, we performed a manual verification process where each row was examined to determine the accuracy of the sentiment value. Also, we performed a similar manual verification for the Y dataset using the same lexicon and application structure. However, the results showed a slight difference compared to the previous data set. The sentiment estimation accuracy of data set Y is 89.42%. A relatively small percentage, 10.58% of comments, were not rated correctly in terms of their sentiment.

Table 2: Results of sentiment evaluation according to accuracy and missing comments identification.

Evaluation	X dataset					Y dataset				
Sentiment	**Positive**	**Neutral**	**Negative**	**Accuracy**	**Missing comments evaluation shown in %**	**Positive**	**Neutral**	**Negative**	**Accuracy**	**Missing comments evaluation shown in %**
Accurate evaluation	263	239	766			77	53	250		
Wrong evaluation	9	12	37	95.62%	4.38%	3	14	28	89.42%	10.58%

Further, in Figure 2, the results are presented in the form of a diagram illustrating the distribution of the three sentiment categories in the case of the X dataset. This visual representation provides insights into how sentiments are distributed within different categories such as negative, neutral, and positive.

As previously explained, the model achieved a 95.62% correct sentiment estimation in the case of dataset X. The comments evaluated in this dataset exhibited the following polarity classification: 60.41% were negative, 18.85% were neutral, and 20.74% were positive comments. However, in 4.38% of the dataset, the model was unable to make accurate evaluations. Upon manual inspection, it was noted that the model occasionally misclassified positive comments as negative, and vice versa. In this subgroup, the polarity distribution was as follows: 63.79% were positive comments, 20.68% were neutral comments, and 15.53% were negative comments.

Figure 2: General results of performing VADER model of X dataset.

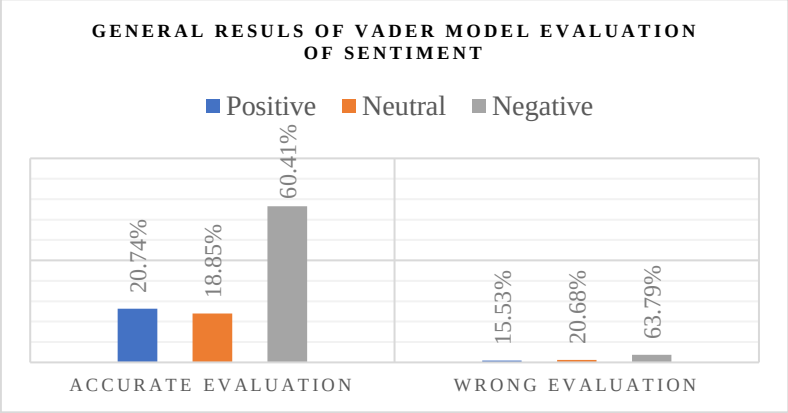
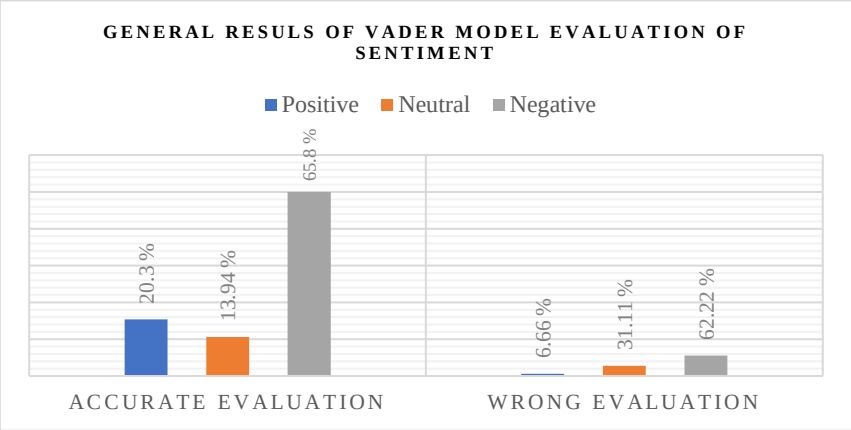


Figure 3 illustrates the distribution of the data set Y through a graphical representation. In addition, it presents a visual depiction of both forms of assessing (correct and incorrect assessing), comments that were correctly classified, and those that the VADER model struggled to accurately classify in terms of sentiment.

Figure 3: General results of performing VADER model of Y dataset.



Similarly, as in the case of dataset X, we have used the same methodology to find the evaluation of the model in the other case of the dataset we have. So, in the case of the Y dataset, the accurate part of comments model has been estimated with 89.42% (see table 2) of the comments as correctly classified by the VADER model. The distribution of comments according to the model's evaluation shows variations compared to the previous case. In the case of Y dataset, there is a higher concentration of negative comments, accounting for a total of 65.8%, whereas positive comments make up 20.3% of the dataset, and lastly, neutral comments represent only 13.9%. These results are presented in Table 3, which includes the precise number of comments for each sentiment classification.

Table 3: Results of sentiment evaluation according to accuracy for each sentiment classification of X and Y dataset.

Evaluation form	X Dataset			Y Dataset		
	Positive	**Neutral**	**Negative**	**Positive**	**Neutral**	**Negative**
Accurate evaluation	263	239	766	77	53	250
Percentage of evaluation per sentiment	20.7%	18.8%	60.4%	20.3%	13.9%	65.8%

Additionally, we have examined the outcomes related to the misclassification of comments, specifically in cases where a comment with negative content was inaccurately classified as neutral or positive. Upon analysis, it becomes evident that a majority of comments are labeled as negative, representing 63.79% of the total comments in dataset X. Neutral comments account for 20.69% of the dataset, while positive comments are the least frequent, constituting 15.52% of the dataset. In the case of dataset Y, 62.2% of comments were incorrectly identified as negative, 31.1% as neutral, and 6.7% as positive comments. A comprehensive overview of the results for both datasets is provided in Table 4.

Table 4: Results of sentiment evaluation according to missing classification sentiment for X and Y dataset.

Evaluation form	X dataset			Y dataset		
	Positive	**Neutral**	**Negative**	**Positive**	**Neutral**	**Negative**
Wrong evaluation	9	12	37	3	14	28
Percentage of evaluation per sentiment	15.52%	20.69%	63.79%	6.7%	31.1%	62.2%

CONCLUSIONS

In this research, we tried to evaluate the sentiment expressed in the sentence written in the Albanian language, as a low - language resources language. To achieve this, we have created a lexicon for different combinations of words in small and clear sentences and for this purpose we have used the VADER lexicon building method. According to VADER, we built a lexicon, consisting of 9500 verbs and adjectives, as well as unigram and bigram expressions. Each verb in the lexicon is assigned a weight that indicates its sentiment as positive, negative, or neutral. This weight is further augmented by an intensity value, which indicates the degree of positivity, neutrality, or negativity expressed in a comment. To test our constructed lexicon, we have used two case studies, namely we have collected social media posts of two companies from the Republic of Kosovo. The purpose of collecting these datasets was more. First, we used unsupervised machine learning methods to cluster comments (posts) based on the topic discussed respectively to find discussion topics. And the second step was to assess the sentiment expressed in that discussion group, namely that set of comments. It is important to mention here that one of the obstacles in doing this was dealing with local and non-standardized ways of speaking and writing. To be sure, we have included in our work a language expert and we have also provided a manual review of the comments.

The companies we named X and Y. For dataset X, approximately 95.6% of comments were correctly estimated by the model, resulting in their sentiment being correctly identified. Only a small fraction, about 4.37% of the comments were estimated incorrectly, leading to a different opinion classification than expected. While for dataset Y, the margin of error is slightly higher as the amount of data is less than in the case of dataset X. The estimation accuracy for dataset Y is 89.41% while missing and wrong estimate percentage is 10.58%. This means that, at this stage of the preparation of the lexicon and considering that the comments are not written in a standard form, the level of accuracy of the VADER Model is adequate.

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