APPLYING BERT AND VADER IN HR SENTIMENT ANALYSIS

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ABSTRACT

In today's business world, it's more important than ever to understand how employees feel. This study delves into the efficacy of open-source tools for sentiment analysis of employee feedback. We devised a Python-based solution, employing BERT and VADER libraries to process and analyze textual data. Our research reveals significant disparities in the sentiment polarity results obtained from these tools, with BERT showing a positivity bias and VADER offering a more balanced sentiment distribution. These findings highlight the importance of selecting appropriate tools for sentiment analysis tasks, tailored to the specific nature of the text. Overall, our study demonstrates the viability and importance of open-source tools in sentiment analysis, particularly in enhancing continuous feedback mechanisms within organizational contexts.

Keywords: *HR analytics, Python, sentiment analysis, BERT, VADER*

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INTRODUCTION

In the rapidly evolving landscape of the corporate world, the ability to understand and interpret employee sentiments has emerged as an important aspect of effective human resource management. The rise of sentiment analysis, also known as opinion mining, represents a significant advancement in this regard. This computational approach to studying people's opinions, sentiments, evaluations, attitudes, moods, and emotions has become increasingly relevant (Liu, 2017). Its growing importance is attributed to its potential to reduce computational costs while simultaneously enhancing the accuracy of data analysis (Satheesh Kumar Rajan et al., 2021).

The significance of this study lies in its exploration of the effectiveness of sentiment analysis in the domain of human resources. With the corporate environment becoming more complex and dynamic, organizations are seeking more efficient ways to gauge and respond to employee sentiments. This is not only to foster a positive work environment but also to make informed decisions that can impact overall productivity and employee satisfaction. By leveraging sentiment analysis, human resource departments can gain deeper insights into the emotional and psychological states of their employees, leading to more nuanced and effective management strategies.

This article aims to provide an evaluation of sentiment analysis tools, particularly focusing on their application in human resource management. It seeks to show how these tools can be effectively utilized to analyze employee feedback, thereby offering valuable insights for organizational development and decision-making.

The study involved gathering and analyzing employee reviews to apply and analyze various sentiment analysis techniques. This meticulous approach provided a foundation for a detailed examination of the results, revealing significant insights into the effectiveness and limitations of different sentiment analysis tools. Particularly, it brought to light the disparities in sentiment assessments between tools like BERT and VADER, each demonstrating distinct biases and capabilities in interpreting employee feedback. The analysis delved into these nuances, uncovering the strengths and weaknesses of each approach and their implications for practical applications in human resource management.

In discussing these results, the article not only highlights the key findings but also critically examines their broader implications. It explores how these insights can influence the way organizations approach employee sentiment analysis, potentially leading to more informed and effective HR strategies. Moreover, the study's conclusions draw attention to the importance of selecting appropriate tools for sentiment analysis, tailoring them to the specific nature and context of the text being analyzed.

1. THE ROLE OF SENTIMENT ANALYSIS IN HR

The importance of understanding and addressing employee sentiments cannot be overstated. The digital age has brought forth a multitude of tools and techniques to assess these sentiments, with sentiment analysis emerging as a frontrunner. Sentiment analysis, often interchangeably used with the term 'opinion mining', is a computational approach to deciphering people's opinions, sentiments, evaluations, attitudes, moods, and emotions from written text (Liu, 2017).

Historically, human resource departments relied heavily on traditional methods such as surveys, face-to-face interviews, and feedback forms to understand employee sentiments. While these methods provided valuable insights, they were often time-consuming, prone to biases, and lacked real-time feedback. The advent of sentiment analysis has revolutionized this paradigm. By leveraging natural language processing and machine learning algorithms, sentiment analysis offers a more efficient, unbiased, and instantaneous way to understand employee sentiments (Rajan et al., 2021).

The integration of sentiment analysis into HR systems has had profound implications for firm performance. Choi (2019) highlighted that HR systems significantly influence the performance of firms. More importantly, a positive perception of these HR systems by employees mediates the relationship between HR and performance. This underscores the importance of sentiment analysis as a tool to estimate and enhance this positive perception.

Furthermore, the rise of social media and online platforms has provided HR departments with vast amounts of unstructured data, such as employee reviews, comments, and discussions. Sentiment analysis tools have become indispensable in mining these vast datasets to extract meaningful insights about employee sentiments, concerns, and suggestions (Sudhir & Deshakulkarni Suresh, 2021).

Here are some of the important benefits of employing sentiment analysis in HR:

Real-time Feedback: Traditional methods of gathering employee feedback, such as surveys or interviews, often suffer from time lags. Sentiment analysis, on the other hand, provides real-time insights into employee sentiments, allowing HR professionals to address concerns promptly (Rocca, Giacomini, & Zola, 2020).

Objective Analysis: Human biases can often creep into traditional methods of sentiment assessment. Sentiment analysis offers an objective and unbiased analysis of employee sentiments, ensuring that the insights derived are accurate and free from personal biases (Rajan et al., 2021).

Data-driven Decision Making: With sentiment analysis, HR departments can make decisions based on concrete data rather than intuition. This data-driven approach ensures that strategies and interventions are more aligned with actual employee needs and sentiments (Sudhir & Deshakulkarni Suresh, 2021).

Enhanced Employee Engagement: By continuously monitoring and addressing employee sentiments, organizations can foster a more engaged and satisfied workforce. Positive sentiment feedback can be used to reinforce successful HR practices, while negative feedback can guide interventions to improve employee satisfaction (Choi, 2019).

Cost-effective: Sentiment analysis tools, especially when automated, can be more cost-effective in the long run compared to traditional methods. They minimize computational expenses and can process vast amounts of data without significant manual intervention (Rajan et al., 2021).

Strategic Planning: Insights derived from sentiment analysis can be instrumental in strategic HR planning. Understanding overarching sentiment trends can guide HR policies, training programs, and organizational change initiatives (Liu, 2017).

In essence, sentiment analysis equips HR professionals with a powerful tool to understand the pulse of their organization. By tapping into the myriad benefits of this technology, HR departments can ensure a more harmonious, engaged, and productive workplace.

2. KEY TOOLS FOR HR SENTIMENT ANALYSIS

In data science, open-source tools help organizations understand and use their data (Provost, F., & Fawcett, T., 2013) and they can become pivotal in understanding employee sentiments. Python modules such as Pandas, NumPy, and scikit-learn, along with R and its packages, offer pliable data processing and visualization for HR sentiment analysis. The affordability of open-source technologies, in comparison to pricey proprietary software, allows

HR professionals to employ advanced methods, algorithms, and models in their sentiment analysis tasks. Owing to the collaborative nature of the open-source community, these tools are routinely updated, enabling HR departments to stay updated with the latest advancements in sentiment analytics (Peng, R. D., & Matsui, E., 2016). By leveraging these open-source tools, HR professionals can derive meaningful insights into employee sentiments, aiding in informed decision-making and enhancing workplace culture.

Free platforms like R, Python, and Weka have gained traction in HR sentiment analytics due to their accessibility and versatility (Wickham & Grolemund, 2017).

Various techniques exist for sentiment analysis in HR contexts. One method is utilizing TextBlob, esteemed for its simplicity, which operates on a lexicon-based sentiment foundation. An alternative method is the adoption of the BERT model, an avant-garde, context-sensitive tool, showing expertise in discerning complex textual dynamics (Devlin et al., 2018; Loria, n.d.; Sun et al., 2019). BERT is frequently employed as a primary layer for generating vector representations of words in feedback or comments. Its attention mechanism ensures varied representations of the same word based on context, proving advantageous in capturing intricate textual relationships in employee feedback. BERT's outputs have been used to predict aspects of HR sentiment, such as emotional tone and specific domains of feedback (Devlin et al., 2019; Colasanto et al., 2022; Phan & Ogunbona, 2020; Karimi, Rossi & Prati, 2021; Xu et al., 2020). Recent models like DomBERT have been developed to maximize BERT's potential in detecting specific sentiment aspects, marrying it with linguistic theories (H. Xu et al., 2020; Wu et al., 2019; Li et al., 2019). This combination of BERT's contextual depth with linguistic techniques strives to elevate the precision of sentiment aspect recognition in HR evaluations.

To analyze the sentiment of article headlines, we utilized the Valence Aware Dictionary for Sentiment Reasoning (VADER) tool in conjunction with a Python script. Following this, we used the Python Data Analysis Library (Pandas) to evaluate and compute a sentiment score. VADER (Valence Aware Dictionary for Affective Reasoning) is a rule-based model that can be used for general sentiment analysis (Aljedaani et al., 2022). Its sensitivity to polarity and sentiment intensity can be used on unlabeled text data. VADER is included in the NLTK package, a platform for building Python programs that process human language data (https://www.nltk.org/). VADER retains and improves the advantages of traditional sentiment dictionaries such as LIWC (Linguistic Query and Word Count). VADER differs from LIWC in that it has better generalization ability to different domains and pays more attention to emotional expression in social media environments. (Hutto, C.J. and Gilbert, 2014) were able to create and empirically validate a set of lexical features that are particularly sensitive to sentiment in a Weibo-like context. Therefore, VADER can be used to perform sentiment analysis on financial news headlines published online and shared on social media.

3. DATA COLLECTION AND ANALYSIS

The primary data for this research was collected from indeed.com, where a random sample of 150 reviews about the workplace environment in the company was amassed. Also, in order to be able to do relevant sentiment analysis we selected only those reviews that had at least 40 characters in length. The reviews were specific to three companies: LIDL, KAUFLAND, and CARREFOUR in Romania. Once the reviews were collected, they were arranged in an Excel file with separate sheets for each company, ensuring a structured format for data processing.

For sentiment analysis, the open-source tools BERT (through the 'transformers' library) and VADER were chosen for their efficiency and ease of use in processing textual data.

The results were analyzed using methodological analysis techniques, such as scatter plots analysis and parametric and nonparametric correlations. Regressions were also considered, but without success.

Both for BERT and VADER analysis we have used the Python programming language. For BERT, the libraries considered were: transformers (including RobertaTokenizer and RobertaForSequenceClassification), pipeline, pandas, and matplotlib.pyplot, while for VADER, we have used the next libraries: pandas, vaderSentiment (including SentimentIntensityAnalyzer), and matplotlib.pyplot.

Next, the code for achieving the BERT results is exposed:

```
import pandas as pd

import matplotlib.pyplot as plt

from transformers import RobertaTokenizer, RobertaForSequenceClassification,
pipeline
```

Load the tokenizer and model for RoBERTa

```
model_name = 'roberta-base'

tokenizer = RobertaTokenizer.from_pretrained(model_name)

model = RobertaForSequenceClassification.from_pretrained(model_name)
```

Load the sentiment-analysis pipeline using RoBERTa

```
sentiment_analysis = pipeline("sentiment-analysis", model=model,
tokenizer=tokenizer)
def analyze_sentiment_with_roberta(text: str):
    # Truncate the text to fit within RoBERTa's limit
    truncated_text = text[:512]

    result = sentiment_analysis(truncated_text)[0]
    label = result['label']
    score = result['score']
    # Convert the label to Positive, Neutral, Negative for consistency
    # Adjust the labels according to the RoBERTa's output
    if label == "NEGATIVE":
        return 'Negative', score
    else:
        return 'Positive', score
def analyze_reviews_for_sheet(sheet_name, xls):
    reviews = xls.parse(sheet_name)
    sentiments = []
    scores = []
    for review in reviews['Review']:
        sentiment, score = analyze_sentiment_with_roberta(review)
        sentiments.append(sentiment)
        scores.append(score)
    reviews['Sentiment'] = sentiments
    reviews['Score'] = scores
    # Plotting Review Score
    reviews['Score'].plot(kind='line', title=f'{sheet_name} Review Sentiment
Score')
    plt.show()
    return reviews
def main():
    # Read Excel file with multiple sheets
    xls = pd.ExcelFile('reviews.xlsx')

    # Analyze sentiment for each sheet and save results to a new Excel file
    with pd.ExcelWriter('reviews_with_sentiment_roberta.xlsx') as writer:
        for sheet_name in xls.sheet_names:
            analyzed_reviews = analyze_reviews_for_sheet(sheet_name, xls)
            analyzed_reviews.to_excel(writer, sheet_name=sheet_name, index=False)
if __name__ == "__main__":
    main()
import pandas as pd
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
import matplotlib.pyplot as plt

def analyze_sentiment(text: str):
    analyzer = SentimentIntensityAnalyzer()
    sentiment = analyzer.polarity_scores(text)
    return sentiment['compound']  # You can also return the entire sentiment
dictionary if needed
```

```
def analyze_reviews_for_sheet(sheet_name, xls):
    reviews = xls.parse(sheet_name)
    polarities = [analyze_sentiment(review) for review in reviews['Review']]

    reviews['Polarity'] = polarities

    # Calculate average polarity after analyzing all reviews in the sheet
    average_polarity = sum(polarities) / len(polarities) if len(polarities) != 0
else 0

    return reviews, average_polarity

def main():
    # Read Excel file with multiple sheets
    xls = pd.ExcelFile('reviews.xlsx')
    average_polarities = {}

    # Analyze sentiment for each sheet and save results to a new Excel file
    with pd.ExcelWriter('reviews_with_sentiment_vader.xlsx') as writer:
        for sheet_name in xls.sheet_names:
            analyzed_reviews, avg_polarity =
analyze_reviews_for_sheet(sheet_name, xls)
            average_polarities[sheet_name] = avg_polarity
            analyzed_reviews.to_excel(writer, sheet_name=sheet_name, index=False)

    # Plotting average sentiment polarity of all sheets
    plt.bar(average_polarities.keys(), average_polarities.values())
    plt.title('Average Sentiment Polarity by Sheet')
    plt.ylabel('Average Polarity')
    plt.xticks(rotation=45, ha='right')
    plt.tight_layout()
    plt.show()
```

4. RESULTS

In table 1 to 3, the descriptive statistics for the two results sets are exposed, firstly for LIDL, Carrefour and Kaufland cases. It can be observed that the mean for BERT is 0.99, and a standard deviation from 0.12 to 0.47, while for VADER, the mean is 0.4, 0.29 and 0.03, with a standard deviation of 0.5-0.7. We can imply the hypothesis that the BERT results are biased and score more positively than the real sentiment score of the entitled news analyzed, while for the difference in mean between VADER and BERT, for the Kaufland case, it can be observed that the BERT results are highly positive, while the VADER results are highly negative. Thus, most probably, bots of the results are biased.

Table 1.

LIDL descriptive statistics of BERT and VADER results
Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
BERT	50	0	1	.99	.012
VADER	50	-1	1	.40	.630
Valid N (listwise)	50				

Table 2.

CAREFOUR descriptive statistics of BERT and VADER results
Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
BERT	50	0	1	.99	.047
VADER	50	-1	1	.29	.548
Valid N (listwise)	50				

Table 3.

Kaufland descriptive statistics of BERT and VADER results
Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
BERT	50	0	1	.99	.039
VADER	50	-1	1	.03	.616
Valid N (listwise)	50				

Next, in figures 1 to 3, scatter plots with the data are exposed. From the graphs it can be observed a low, positive, linear relationship among the two variables, in case of LIDL, but no relationship in case of Carrefour and Kaufland. We will further analyze this results using parametric and nonparametric correlation.

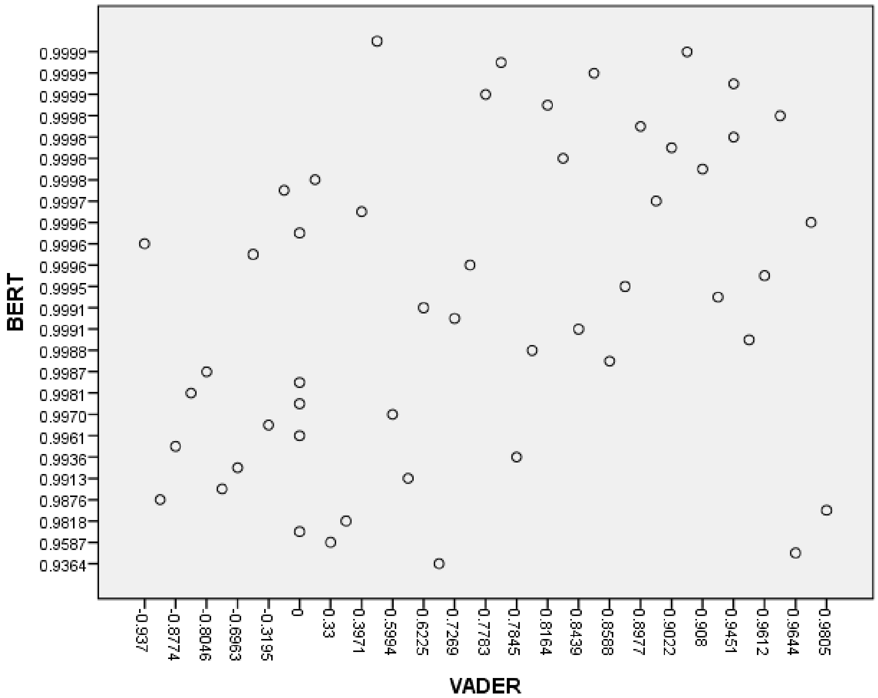

Figure 1. LIDL scatter plot of BERT and VADER results

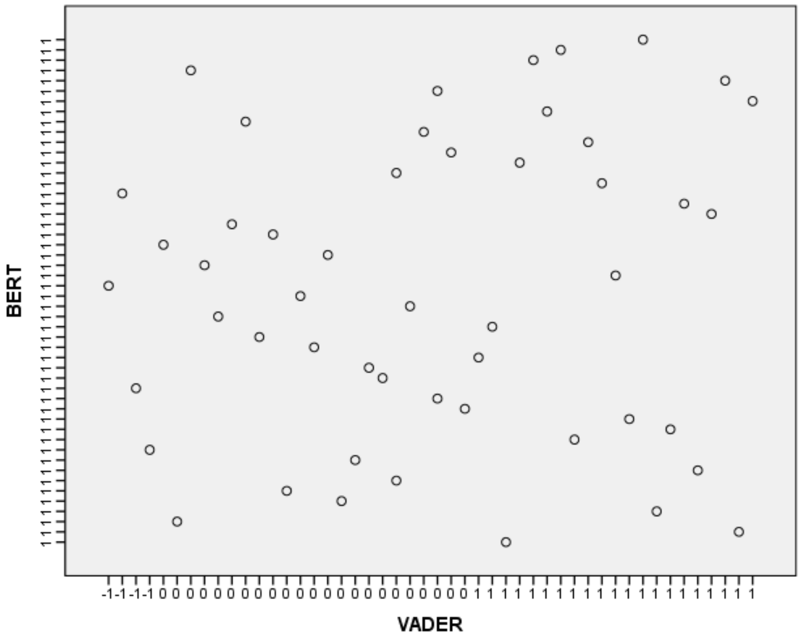

Figure 2. Carrefour scatter plot of BERT and VADER results

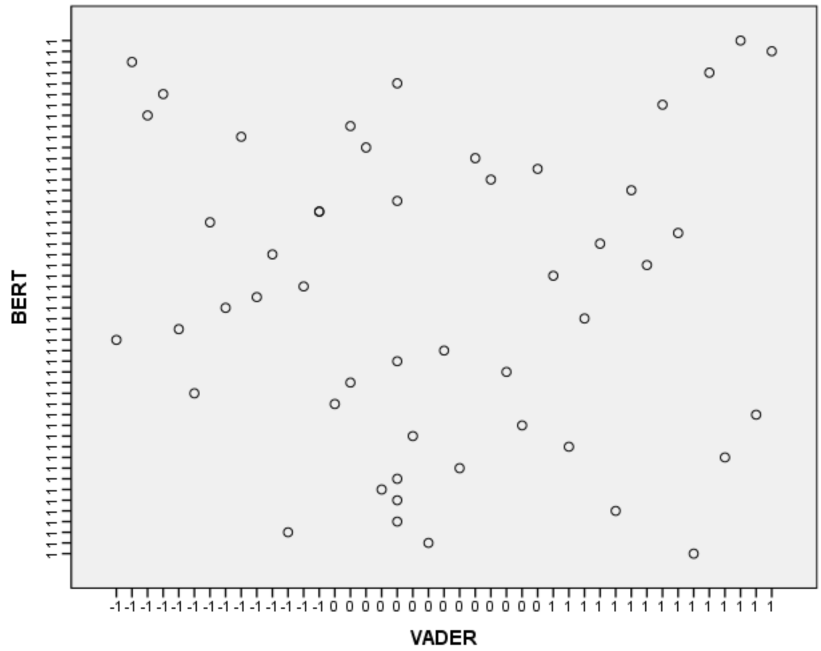

Figure 3. Kaufland scatter plot of BERT and VADER results

Next, parametric correlation, using Pearson procedure and nonparametric correlations were performed, using Kendall and Spearman correlation.

Table 4.

LIDL Pearson correlation for BERT and VADER results

Correlations

		BERT	VADER
BERT	Pearson Correlation	1	.015
	Sig. (2-tailed)		.919
	N	50	50
VADER	Pearson Correlation	.015	1
	Sig. (2-tailed)	.919	
	N	50	50

Results from table 4 show a nonsignificant positive correlation among the BERT and VADER results, in case of LIDL. In contrast, the nonparametric correlation show us a significant positive correlation among the two result sets (of 0.251 and 0.365, with significance level under 0.1).

Table 5.

LIDL nonparametric correlations for BERT and VADER results

Correlations

			BERT	VADER
Kendall's tau_b	BERT	Correlation Coefficient	1.000	.251*
		Sig. (2-tailed)	.	.010
		N	50	50
	VADER	Correlation Coefficient	.251*	1.000
		Sig. (2-tailed)	.010	.
		N	50	50
Spearman's rho	BERT	Correlation Coefficient	1.000	.365**
		Sig. (2-tailed)	.	.009
		N	50	50
	VADER	Correlation Coefficient	.365**	1.000
		Sig. (2-tailed)	.009	.
		N	50	50

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

In table 6 and 7, both the parametric and nonparametric correlation coefficients among the BERT and AVDER results are nonsignificant, in case of Carrefour.

Table 6.

Carrefour Pearson correlation for BERT and VADER results

Correlations

		BERT	VADER
BERT	Pearson Correlation	1	-.123
	Sig. (2-tailed)		.397
	N	50	50
VADER	Pearson Correlation	-.123	1
	Sig. (2-tailed)	.397	
	N	50	50

Table 7.

Carrefour nonparametric correlation for BERT and VADER results

Correlations

			BERT	VADER
Kendall's tau_b	BERT	Correlation Coefficient	1.000	.056
		Sig. (2-tailed)	.	.564
		N	50	50
	VADER	Correlation Coefficient	.056	1.000
		Sig. (2-tailed)	.564	.
		N	50	50
Spearman's rho	BERT	Correlation Coefficient	1.000	.106
		Sig. (2-tailed)	.	.464
		N	50	50
	VADER	Correlation Coefficient	.106	1.000
		Sig. (2-tailed)	.464	.
		N	50	50

In table 8 and 9, both parametric and nonparametric correlation coefficients are insignificant, thus there is no correlation among the BERT and VADER results, in case of Kaufland sentiment score.

Table 8.

Kaufland Pearson correlation for BERT and VADER results

Correlations

		BERT	VADER
BERT	Pearson Correlation	1	-.189
	Sig. (2-tailed)		.189
	N	50	50
VADER	Pearson Correlation	-.189	1
	Sig. (2-tailed)	.189	
	N	50	50

Table 9.

Kaufland nonparametric correlation for BERT and VADER results

Correlations

			BERT	VADER
Kendall's tau_b	BERT	Correlation Coefficient	1.000	-.026
		Sig. (2-tailed)	.	.789
		N	50	50
	VADER	Correlation Coefficient	-.026	1.000
		Sig. (2-tailed)	.789	.
		N	50	50
Spearman's rho	BERT	Correlation Coefficient	1.000	-.048
		Sig. (2-tailed)	.	.739
		N	50	50
	VADER	Correlation Coefficient	-.048	1.000
		Sig. (2-tailed)	.739	.
		N	50	50

5. DISCUSSION

The significance of sentiment analysis in various domains has been increasingly recognized in recent years. This study's exploration of open-source tools for sentiment analysis, specifically focusing on employee feedback from three companies, aligns with the broader trend in the research community. Several studies have delved into the effectiveness, reliability, and application of sentiment analysis tools.

For instance, Novielli et al. (2020) evaluated the performance of sentiment analysis tools in a software engineering context and found that lexicon-based tools often outperform supervised approaches in certain settings. This underscores the importance of choosing the right tool based on the specific context and data at hand. Another study by Rocca et al. (2020) highlighted the potential of sentiment analysis in supporting environmental reporting, emphasizing its cost-effectiveness and speed compared to traditional surveys Rocca et al., 2020.

However, it's important to approach sentiment analysis with caution. Boukes et al. (2019) concluded that off-the-shelf sentiment analysis tools might be unreliable for specific languages and domains, emphasizing the need for manual validation. This resonates with the methodology of our study, where we tailored a Python script specifically for employee feedback.

In the area of open-source software, sentiment analysis has been utilized frequently, with numerous tools utilizing support-vector machines. This further validates our decision to conduct our analysis using the open-source tool BERT and VADER.

A striking observation is the substantial variance in mean sentiment scores between BERT and VADER. BERT consistently showed a higher mean close to 0.99 across all three brands, indicating a strong positive bias. This high mean could suggest that BERT is overly sensitive to positive sentiments or is not as effective in distinguishing neutral or slightly positive sentiments from highly positive ones. On the other hand, VADER's means (0.4, 0.29, and 0.03 for LIDL, Carrefour, and Kaufland, respectively) were significantly lower, suggesting a more moderate and potentially more realistic sentiment assessment. The standard deviation in VADER's results was higher, indicating a broader range of sentiment values.

The Pearson correlation analysis for LIDL revealed a non-significant positive correlation between BERT and VADER, suggesting little to no linear relationship in their sentiment assessments. This observation was echoed in the cases of Carrefour and Kaufland, where both parametric and nonparametric correlations were found to be nonsignificant. These findings underscore the disparity in how BERT and VADER evaluate sentiments.

The different approaches of BERT and VADER in processing and interpreting sentiment could be a contributing factor to the observed discrepancies. BERT, a model based on the transformer architecture, is more context-aware and could be overemphasizing certain contextual elements, leading to a positivity bias. VADER, designed specifically for social media texts, may offer a more balanced view, particularly adept at handling informal language, emojis, and slangs, which are commonly found in employee reviews.

Thus, the results show a highly trustable results in case of VADER results, while the two result sets were significantly correlated in only one case of the three cases analyzed.

CONCLUSION

The comparative study of BERT and VADER sentiment analysis tools reveals significant differences in their assessment of customer sentiments across three major retail brands. BERT exhibited a consistent positivity bias, whereas VADER presented a more balanced sentiment distribution. The lack of significant correlation between the tools’ results indicates that they may be suited for different types of sentiment analysis tasks.

For practitioners and researchers in sentiment analysis, these findings highlight the importance of choosing the right tool based on the specific requirements and nature of the text being analyzed. For nuanced and context-heavy texts, BERT might be preferred, albeit with caution regarding its positivity bias. In contrast, for more straightforward, informal texts, VADER might offer a more realistic sentiment assessment.

Future studies could explore combining the strengths of both tools or adjusting their algorithms to mitigate biases, thereby enhancing the accuracy and reliability of sentiment analysis in various domains. Additionally, exploring the impact of different types of data (such as long-form reviews vs. short social media posts) on these tools' performance would be a valuable area of research.

In conclusion, sentiment analysis is a strong tool for interpreting emotions and views from textual data, but the results show that the instrument and its application must be context-specific. Our research contributes to this growing field by showcasing the potential of open-source tools in analyzing employee feedback, emphasizing the importance of continuous feedback mechanisms in organizational settings. Future research could focus on developing these tools for even more particular scenarios or investigating their interaction with other data analysis techniques.

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