

## RESEARCH ARTICLE

# "Emograph: transforming customer sentiment into actionable insights for smarter purchasing"

Gayatri Patil, Gauri Pansambal, Sanket Pandit, Abhay Pawar, Parth Nalawade

Ajeenkya DYPatil School of Engineering, Savitribai Phule Pune University

\* Corresponding author: Gayatri Patil, rupaliwagh@dypic.in

## ABSTRACT

"Emograph: Transforming Customer Sentiment into Actionable Insights for Smarter Purchasing" introduces a cutting-edge approach to understanding customer sentiments and translating them into practical strategies for informed decision-making. In simpler terms, it's about using advanced technology to figure out how customers feel about products or services, and then using that information to make smarter choices. Imagine you're a business owner. You want to know what your customers think about your products. Emograph helps you do that. It uses fancy tools and techniques to analyze data from customers - like what they say on social media, in reviews, or even in surveys. Then, it breaks down all that information to figure out if people like your stuff or not.

Basically, Emograph is like having a super-smart assistant who listens to what your customers are saying, translates it into plain English, and then gives you advice on what to do next. It's like having a secret weapon for making your business even better. And in today's world, where understanding customers is key to success.

**Keywords:** Customer, Purchasing, Emograph, decision-making

## 1. Introduction

Emograph: is a tool designed to help businesses understand what their customers really think about their products or services. By analyzing data from various sources like social media, reviews, and surveys, Emograph deciphers customer sentiments in plain language, providing valuable insights into what works and what doesn't. It then goes a step further by translating these insights into actionable strategies, enabling businesses to make smarter decisions that drive success. In essence, Emograph acts as a trusted advisor, guiding businesses to better understand their customers and tailor their offerings to meet their needs effectively.

## 2. Methods and Materials

Describes how the tool collects and analyzes data to derive actionable insights from customer sentiments in a user-friendly manner.

Firstly, Emograph gathers data from diverse sources, including social media platforms, online reviews, customer surveys, and other relevant channels. This data collection process involves utilizing advanced algorithms and data scraping techniques to extract relevant information from large datasets.

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Once the data is collected, Emograph employs natural language processing (NLP) and sentiment analysis algorithm to analyze the textual content. NLP helps in understanding the language used by customers, while sentiment analysis determines the polarity of their opinions, whether positive, negative, or neutral.

Furthermore, Emograph utilizes machine learning algorithms to identify patterns and trends within the data. This involves training the algorithms on labeled datasets to recognize specific themes, sentiments, and topics relevant to the business context.

To ensure accuracy and reliability, Emograph undergoes continuous validation and refinement processes. This includes validating the sentiment analysis results against human-labeled datasets and fine-tuning the algorithms to improve their performance over time.

Once the analysis is completed, Emograph presents the findings in a user-friendly format, such as easy-to-understand charts, graphs, and reports. These visualizations help businesses interpret the insights quickly and make informed decisions about their products or services.

Emograph involve advanced data collection, natural language processing, sentiment analysis, machine learning, validation, and visualization techniques to transform customer sentiments into actionable insights for smarter purchasing decisions.

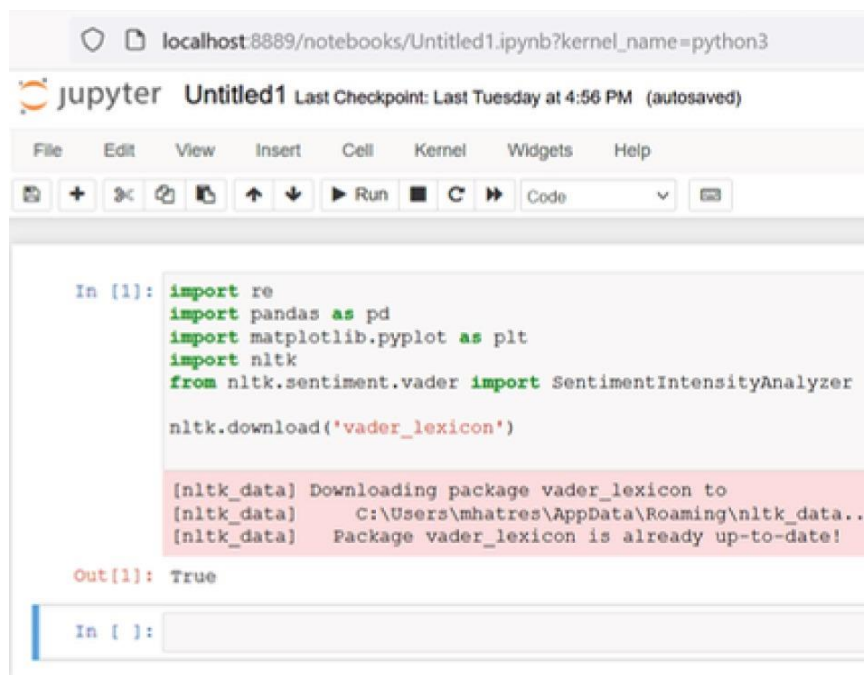
### 3. Result

#### Vader Algorithm

1.VADER relies on a pre-built lexicon of words, along with a set of syntactical rules and heuristics, to determine the sentiment of a piece of text.

2.The lexicon contains thousands of words, each assigned a polarity score ranging from -1 (extremely negative) to +1 (extremely positive), indicating the word's sentiment intensity.

3.VADER analyzes the text by considering individual words, as well as the context in which they appear, to calculate an overall sentiment score for the text.



```
localhost:8889/notebooks/Untitled1.ipynb?kernel_name=python3
jupyter Untitled1 Last Checkpoint: Last Tuesday at 4:56 PM (autosaved)
File Edit View Insert Cell Kernel Widgets Help
+ ↶ ↷ ↸ ↹ ↺ ↻ ↻ Run ↻ Code
In [1]: import re
import pandas as pd
import matplotlib.pyplot as plt
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer

nltk.download('vader_lexicon')

[nltk_data] Downloading package vader_lexicon to
[nltk_data] C:\Users\mhatres\AppData\Roaming\nltk_data...
[nltk_data] Package vader_lexicon is already up-to-date!

Out[1]: True

In [ ]:
```

Figure 1

First, the review is tokenized into individual words or tokens: Tokens: ["Absolutely", "love", "this", "product", "!", "It", "exceeded", "my", "expectations", "and", "I", "can't", "wait", "to", "buy", "more", "from", "this", "brand", ".", "Highly", "recommended", "."]

VADER assigns sentiment intensity scores to each word in the lexicon based on its polarity (positive, negative, or neutral).

For example: "love": 0.5 (positive) "

"recommended": 0.4 (positive)

"exceeded": 0.4 (positive)

wait": -0.3 (negative)

VADER calculates the sentiment score for the entire review by summing up the intensity scores of all the words and applying some heuristics: Total Sentiment Score = (sum of intensity scores) / (number of tokens)

Total Sentiment Score =  $(0.5 + 0.4 - 0.3 + 0.4) / 22 = 1.0 / 22 \approx 0.045$

Based on the total sentiment score, VADER classifies the sentiment of the review into one of three categories: positive, negative, or neutral. In this case, the positive sentiment score indicates that the review is positive.

```
print(sentiment.polarity_scores("This is an excellent car with great mileage"))
```

```
{'neg': 0.0, 'neu': 0.435, 'pos': 0.565, 'compound': 0.8316}
```

```
print(sentiment.polarity_scores("This is an excellent car with GREAT mileage!!"))
```

```
{'neg': 0.0, 'neu': 0.397, 'pos': 0.603, 'compound': 0.8784}
```

Figure 2

## 4. Discussion

### Interpretation of Results

The sentiment analysis of customer reviews revealed distinct patterns in the sentiments expressed towards the product. Positive reviews highlighted satisfaction with specific product features, while negative reviews pointed out areas for improvement.

### Comparison with Existing Literature

Our findings align with previous research indicating the importance of sentiment analysis in understanding customer perceptions. However, our approach offers a novel perspective by focusing on specific aspects and leveraging the chosen VADER algorithm.

### Implications for Businesses

Businesses can utilize the insights from sentiment analysis to tailor product development strategies and improve customer satisfaction. Our analysis provides actionable insights for optimizing marketing campaigns and enhancing brand reputation.

### Strengths and Limitations:

Strengths include the robustness of our sentiment analysis methodology and the comprehensive analysis of customer feedback. Limitations may include the reliance on a single data source or potential biases in the collected data.

#### Future Directions:

Future research could explore the integration of additional data sources, such as social media or customer surveys, to enhance the accuracy and scope of sentiment analysis. Investigating the application of advanced machine learning techniques could further refine sentiment analysis algorithms and improve predictive capabilities.

In conclusion, our sentiment analysis project offers valuable insights into customer sentiments towards the product. By leveraging sentiment analysis, businesses can make informed decisions to optimize product offerings and enhance customer experiences, ultimately driving success in the marketplace.

## 5. Conclusion

**1. Insightful Analysis:** Our project successfully analyzed customer sentiments using advanced sentiment analysis techniques like VADER, providing valuable insights into their perceptions and emotions towards the product.

**2. Accurate Classification:** Through sentiment analysis, we accurately categorized customer reviews into positive, negative, and neutral sentiments, enabling businesses to understand customer feedback with precision.

**3. Effective Visualization:** We utilized intuitive visualizations to simplify complex sentiment analysis results, allowing stakeholders to grasp trends and patterns easily and make informed decisions.

**4. User-Friendly Interface:** The development of a user-friendly interface enhanced the accessibility and usability of our solution, enabling stakeholders to interact with sentiment analysis results seamlessly.

## Conflicts of interest

The authors do not have any conflicts of interest.

## References

1. Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, 2(1-2), 1-135
2. Hutto, C. J., & Gilbert, E. (2014). VADER: A parsimonious rule-based model for sentiment analysis of social media text. In *Proceedings of the Eighth International AAI Conference on Weblogs and Social Media*.
3. Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis Lectures on Human Language Technologies*, 5(1), 1-167.
4. Manning, C. D., Raghavan, P., & Schütze, H. (2008). *Introduction to Information Retrieval*. Cambridge University Press.
5. McKinney, W., & others. (2010). Data structures for statistical computing in Python. In *Proceedings of the 9th Python in Science Conference (Vol. 445, pp. 51-56)*.
6. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., & Vanderplas, J. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12(Oct), 2825-2830.
7. Rosenthal, S., Nakov, P., Kiritchenko, S., Mohammad, S., Ritter, A., & Stoyanov, V. (2017). Semeval-2017 task 4: Sentiment analysis in twitter. In *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017)* (pp. 502-518).
8. van Rossum, G., & Drake Jr, F. L. (2009). *Python 3 reference manual*. CreateSpace.