



# Sentiment Analysis of Customer Reviews Using Flask

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**Abstract:** In today's world, social media is everywhere, and understanding how people feel about things online can be tricky. That's where sentiment analysis comes in. Imagine being able to gauge how people really feel about a brand, a product, or even a political issue just by analyzing what they're saying online. It's not just about understanding; it's about using that knowledge to protect or even boost your online reputation. Keeping this problem in consideration we present a Flask-based web application for sentiment analysis of customer reviews of a clothing brand stored in CSV format. The application employs NLP techniques to analyze sentiment and also performs EDA to provide a comprehensive understanding of customer feedback trends.

**Keywords:** Flask, NLP, EDA, Sentiment

## I. INTRODUCTION

The objective is to create a robust sentiment analysis solution specifically designed for analysing social media content. This solution aims to accurately categorize the sentiment expressed in various forms of social media communication, including posts, comments, and interactions. By leveraging advanced natural language processing and machine learning techniques, the system will be capable of discerning nuances in language and context to provide precise sentiment classifications. Additionally, the solution will offer valuable insights into public perception, customer feedback, and brand reputation, enabling organizations to gain a deeper understanding of their audience's sentiments. To validate its efficacy, the solution will undergo empirical studies and real-world case studies to evaluate its performance and applicability. Practical applications of this sentiment analysis solution include proactive brand monitoring and the development of targeted engagement strategies based on the identified sentiments within social media conversations.

## II. LITERATURE REVIEW

The field of sentiment analysis, also known as opinion mining, has seen significant advancements in recent years, driven by the increasing availability of digital data and the demand for understanding public sentiment. This literature review delves into key studies and developments relevant to developing a comprehensive sentiment analysis solution tailored for social media content.

1. Research by Liu [1] paved the way for sentiment analysis by introducing a comprehensive framework for opinion mining. The study emphasized the importance of natural language processing (NLP) techniques in extracting sentiment from textual data, categorizing sentiments into positive, negative, and neutral categories. This foundational work laid the groundwork for subsequent sentiment analysis methodologies.

2. Pang and Lee [2] contributed significantly to sentiment classification accuracy in social media content. Their research focused on feature-based sentiment analysis, leveraging machine learning algorithms such as Support Vector Machines (SVM) to classify sentiments with high precision. The study highlighted the importance of feature selection and model training in achieving reliable sentiment classification results.

3. Kim et al. [3] explored sentiment analysis's role in understanding public perception and brand reputation on social media platforms. Their study demonstrated how sentiment analysis can uncover actionable insights from customer feedback, identify sentiment trends, and assess brand sentiment across different demographics. The findings underscored the strategic value of sentiment analysis in shaping brand strategies and improving customer satisfaction.

4. Recent advancements in deep learning, particularly with models like BERT [4] and GPT-3 [5], have revolutionized sentiment analysis. These models, based on transformer architectures, excel in capturing contextual nuances and understanding sentiment in complex language structures. Incorporating such advanced NLP techniques into sentiment analysis pipelines can significantly enhance accuracy and versatility.



5. Numerous empirical studies and real-world case studies have showcased the practical applications and effectiveness of sentiment analysis across various domains. For instance, research by Hutto and Gilbert [6] demonstrated sentiment analysis's utility in political discourse analysis, showcasing how sentiment trends can reflect public opinion dynamics during elections. Similarly, industry case studies have highlighted sentiment analysis's role in customer experience management, social listening, and brand sentiment tracking.

These literature insights collectively highlight the evolution and diverse applications of sentiment analysis, underscoring its significance in understanding public sentiment, customer feedback, and brand perception in the digital age. Integrating advanced NLP techniques and machine learning algorithms, coupled with empirical validation through case studies, can enrich your sentiment analysis solution's effectiveness and practicality.

### III. PROBLEM STATEMENT

Sentiment analysis of Social Media presence (This research addresses the need for efficient sentiment analysis of customer reviews in the e-commerce domain. The challenge is to develop a Flask-based application capable of automating sentiment analysis tasks on large datasets, ensuring accuracy, scalability, and usability for businesses seeking to extract valuable insights from customer feedback.)

### IV. REQUIREMENTS

Technologies:

1. Flask (for web interface)
2. Python & ML Libraries (for analysis)

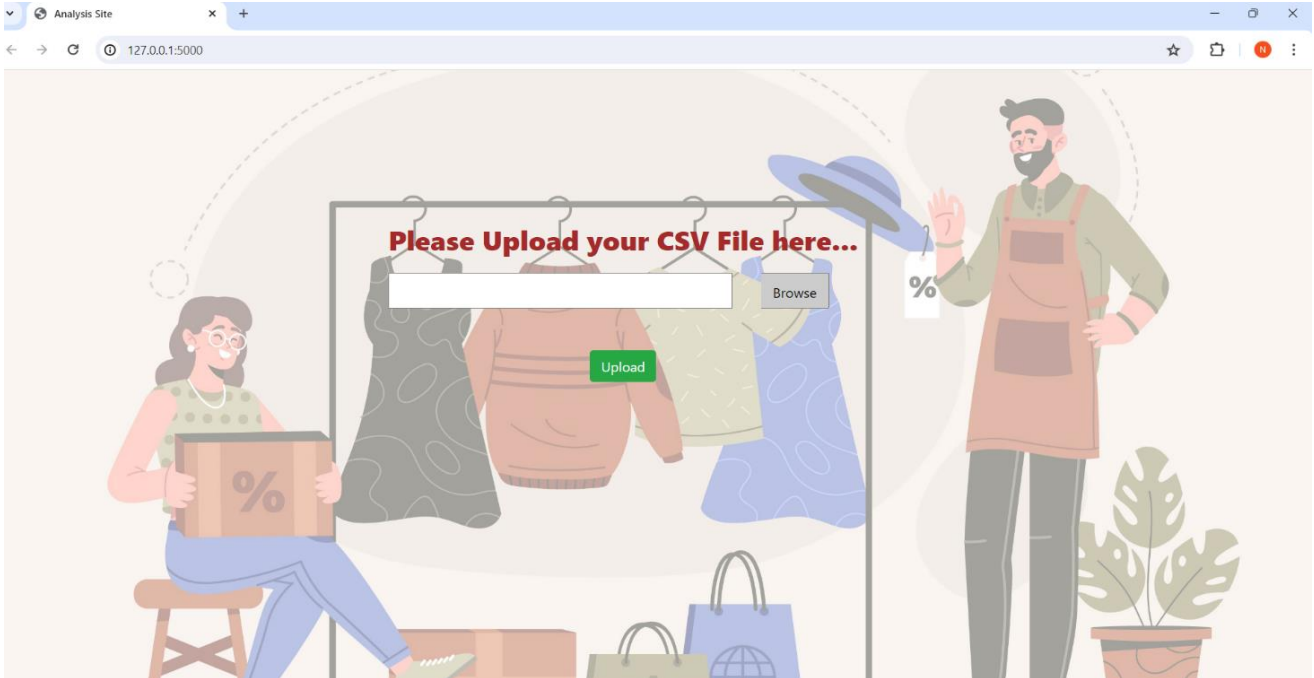
### V. METHODOLOGY

1. Firstly, the user must upload a CSV file containing the dataset of customer review on a web application.
2. After this, the application processes the data to find out valuable insights from the customer review data to perform sentiment analysis.
3. Then a detailed result page is presented containing various key metrics and visualizations.
4. On the result page different sentiment analysis like average polarity and subjectivity scores and sentiment count of reviews into positive, negative, and neutral is shown.
5. Also, some additional analysis like age distribution contains the distribution plot of age, top title contains some top comments used by the customer. Apart from these positive feedback statistics, department counts, and division counts are also shown.

### VI. RESULTS

The Flask application presents users with a user-friendly web interface for conducting sentiment analysis on uploaded CSV files containing customer reviews. Upon file submission, the application processes the data to extract insights from the reviews. Users are presented with a detailed results page encompassing various key metrics and visualizations derived from the analysed data. These metrics include the average polarity and subjectivity scores, offering a comprehensive understanding of the overall sentiment of the reviews.

Additionally, the sentiment category counts provide a breakdown of reviews into positive, negative, and neutral sentiments. The age distribution plot offers insights into the demographics of the customer base, while the top titles analysis highlights the comments of the reviewers. Descriptive statistics of positive feedback counts, and division/department analysis further enrich the insights provided. Through these analyses and visualizations, the application equips users with valuable information to make informed decisions regarding customer satisfaction, demographics, and feedback trends.



### Results

#### Sentiment Analysis:

Average Polarity: 0.24982366680740928

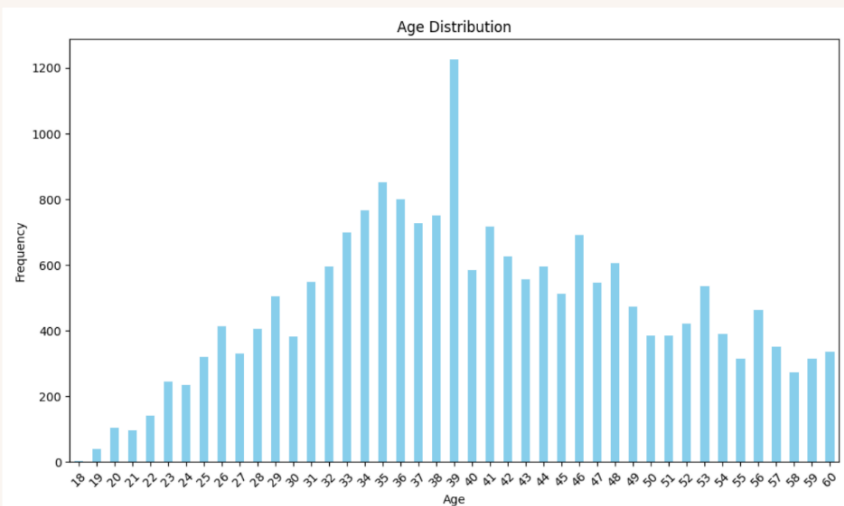
Average Subjectivity: 0.5600454067892684

Sentiment Counts:

- Positive: 21227
- Negative: 1322
- Neutral: 92

#### Additional Analysis:

##### Age Distribution:



**Top Titles:**

- Love it!: 116
- Beautiful: 86
- Love: 84
- Love!: 79
- Beautiful!: 59
- Beautiful dress: 57
- Love it: 51
- Love this dress!: 49
- Cute top: 49
- Disappointed: 47

**Positive Feedback Stats:**

- Count: 20257.0
- Mean: 2.584588043639236
- Standard Deviation: 5.743811958012373
- Minimum: 0.0
- 25th Percentile: 0.0
- Median: 1.0
- 75th Percentile: 3.0
- Maximum: 122.0

**Division Counts:**

- General: 11930
- General Petite: 7016
- Intimates: 1298

**Department Counts:**

- Tops: 8850
- Dresses: 5601
- Bottoms: 3321
- Intimate: 1506
- Jackets: 861
- Trend: 105

## VII. CONCLUSION & FUTURE SCOPE

### Conclusion:

In conclusion, the sentiment analysis Flask application offers businesses valuable insights into customer sentiments and feedback trends from uploaded CSV files. Through calculated metrics and visualizations, it provides actionable data for improving products and services. However, the application may have limitations in accuracy and scalability that require addressing.

### Future Scope:

Future enhancements may include implementing advanced sentiment analysis algorithms, enabling real-time analysis, developing interactive visualizations, incorporating multimodal analysis, integrating with business systems, and optimizing performance for scalability. These improvements can make the application more robust and versatile, enhancing its utility for businesses in understanding and responding to customer feedback effectively.

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