**INTEL PRODUCTS SENTIMENT ANALYSIS FROM ONLINE REVIEWS**

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**INTRODUCTION**

Understanding customer sentiment from online reviews is pivotal for businesses aiming to enhance products, services, and overall customer satisfaction. This report presents a sentiment analysis project focused on extracting actionable insights from a dataset of self-scraped online reviews. The objective is to employ automated techniques to analyse sentiment trends and correlations, providing valuable inputs for strategic decision-making.

**Objectives:**

* Analyse sentiment patterns across a diverse range of self-scraped online reviews.
* Implement advanced sentiment analysis methodologies to capture nuanced expressions of customer sentiment.
* Explore the relationship between sentiment scores and product/service attributes to inform targeted improvements and marketing strategies.

**Methodologies:**

* Utilize NLTK's Vader for baseline sentiment analysis and sentiment intensity scoring.
* Apply RoBERT, a transformer-based model, for deep learning-driven sentiment analysis to uncover subtle sentiment nuances.

**Significance:**

* Automated sentiment analysis enables efficient processing of large-scale textual data, offering insights into customer perceptions and preferences.
* Insights derived from sentiment analysis empower businesses to optimize product offerings, refine marketing campaigns, and enhance overall customer experience.

This report details the methodologies used, data collection processes, preprocessing techniques, and the analysis of sentiment trends derived from the self-scraped online reviews. The findings and implications discussed herein provide actionable solutions for businesses to leverage customer sentiment effectively in decision-making processes.

**LITERATURE REVIEW**

Sentiment analysis, also known as opinion mining, has evolved significantly with the proliferation of digital communication platforms and the increasing importance of customer feedback in business decision-making. This review examines the historical development, methodologies, and applications of sentiment analysis, focusing on its relevance in extracting actionable insights from textual data, particularly self-scraped online reviews. The roots of sentiment analysis can be traced back to early attempts in the 2000s, primarily focused on categorizing text as positive, negative, or neutral based on predefined rules and lexicons. Initial approaches relied heavily on sentiment lexicons and statistical models to assign sentiment scores to individual words and phrases, laying the foundation for lexicon-based sentiment analysis tools like NLTK's VADER.

**Methodologies:**

1. **Lexicon-Based Approaches:** Lexicon-based sentiment analysis utilizes predefined dictionaries of sentiment-laden words and their associated polarity scores to determine the sentiment of a piece of text. Tools such as VADER categorize each word in a sentence and aggregate scores to produce an overall sentiment score. These approaches are valuable for their simplicity and computational efficiency, making them suitable for real-time applications and large-scale datasets.
2. **Machine Learning and Natural Language Processing (NLP):** The advent of machine learning techniques revolutionized sentiment analysis by enabling models to learn sentiment patterns from data. Supervised learning methods, such as Support Vector Machines (SVM) and Naive Bayes classifiers, became popular for their ability to classify sentiments based on labelled training datasets. These models generalize well to new data but require substantial labelled data for training.
3. **Deep Learning and Transformers:** In recent years, deep learning models, particularly transformer-based architectures like BERT (Bidirectional Encoder Representations from Transformers) and RoBERTa, have emerged as state-of-the-art in sentiment analysis. These models leverage large-scale pretraining on vast textual corpora to capture contextual information and semantic nuances, achieving superior performance in sentiment classification tasks. Transformers excel in understanding complex sentence structures and subtle sentiment expressions, making them ideal for sophisticated sentiment analysis applications.

**Applications and Use Cases:** Sentiment analysis finds applications across various domains, including customer feedback analysis, social media monitoring, brand reputation management, and market research. Businesses utilize sentiment analysis to gauge customer satisfaction, identify emerging trends, detect customer sentiment shifts, and tailor marketing strategies accordingly. In healthcare, sentiment analysis aids in understanding patient feedback and improving healthcare services, while in politics and public opinion analysis, it provides insights into public sentiment towards policies and leaders.

**Challenges and Future Directions:** Despite significant advancements, sentiment analysis faces challenges such as handling sarcasm, irony, and context-dependent sentiments, as well as domain adaptation issues. Future research directions include enhancing models' interpretability, addressing bias in sentiment analysis datasets, integrating multimodal data (text, image, video), and exploring sentiment analysis in low-resource languages.

## DATA COLLECTION

The process of data collection for our sentiment analysis project involved systematically scraping online reviews from various platforms. This section outlines the methodologies employed, considerations for ethical scraping practices, and the rationale behind the selection of sources.

**Selection of Platforms:** The first step in data collection was identifying and selecting appropriate platforms from which to scrape online reviews. Platforms were chosen based on their relevance to the products/services under analysis and their popularity among consumers. Sources included e-commerce websites, social media platforms, product review forums, and specialized review aggregators known for hosting authentic user-generated content.

**Ethical Considerations:** Ethical guidelines were paramount throughout the data collection process to ensure compliance with platform terms of service and respect for user privacy. Scraping activities were conducted responsibly, adhering to legal and ethical standards governing data extraction from publicly accessible sources. Measures were taken to prevent overloading servers, avoid disruption of platform operations, and respect robots.txt directives where applicable.

**Scraping Methodology:** Scraping methodologies varied based on the structure and accessibility of each platform. Customized web scraping scripts were developed using Python's selectorlib and Scrapy libraries to automate the extraction of review data. These scripts navigated through pages, parsed HTML content, and extracted relevant information such as review text, ratings, dates, and product/service identifiers.

**Data Filtering and Validation:** Upon extraction, data underwent rigorous filtering and validation processes to ensure quality and reliability. Duplicate reviews, irrelevant content, and non-textual data (e.g., images, advertisements) were filtered out. Validation checks verified the integrity of scraped data against platform-specific guidelines and metadata attributes.

**Handling Dynamic Content and Updates:** To accommodate dynamic content and updates on platforms, scraping scripts were designed to handle pagination, session management, and real-time data synchronization. Regular monitoring and adjustments were made to adapt to changes in website structure, data formats, and anti-scraping measures implemented by platforms.

**Data Storage and Documentation:** Scraped data was stored in structured formats such as CSV files or databases, preserving metadata and source information for traceability and reproducibility. Comprehensive documentation included details of scraping methodologies, platform-specific considerations, and any challenges encountered during data collection.

**DATA PREPROCESSING**

Data preprocessing is a critical step in the data analysis pipeline, ensuring that the data is clean, well-structured, and suitable for analysis. In this project, several preprocessing tasks were performed to prepare the review data for sentiment analysis. This section details each of these steps.

**Data Loading:** The first step involved loading the CSV file containing the review data. Given potential encoding issues, the data was read using multiple encodings until a successful read was achieved. This approach ensured that the data was accurately loaded without any character misinterpretation, which is particularly important for text data like reviews.

**Handling Missing Values:** Missing values in the dataset can significantly affect the analysis results. The review column, being the focus of sentiment analysis, was examined for missing values. These were removed to ensure that only valid reviews were analysed, as any missing or null values could lead to inaccuracies in the sentiment analysis process.

**Data Cleaning:** Data cleaning involved removing any extraneous whitespace and ensuring all reviews were in a consistent format. This step is vital to avoid misinterpretation by the sentiment analysis models. Basic cleaning operations included stripping leading and trailing spaces and converting text to lowercase where necessary. Handling special characters was also a part of this process, ensuring that non-ASCII characters were appropriately managed to prevent any processing issues.

**Identifying the Review Column:** Given the possibility of the review data being stored in different columns across different datasets, a function was used to identify the correct review column by searching for a column containing the keyword "review". This automated identification process ensured that the correct column was selected for analysis, preventing manual errors and improving efficiency.

**Exporting Cleaned Data:** The cleaned data was then exported to a text file for further analysis. This step ensured that the data was available in a simple format for model input and processing. Exporting the data also allowed for easy sharing and collaboration, as well as providing a backup of the cleaned data for future reference.

**Handling Special Characters:** To avoid issues during text processing and analysis, special characters were handled appropriately. This included removing non-ASCII characters and normalizing text where necessary. Handling special characters is essential to maintain the integrity of the text data, ensuring that the sentiment analysis models can accurately interpret and analyse the reviews.

**Final Data Check:** A final check was performed to ensure the data was correctly formatted and free of anomalies. This included verifying the data types, checking for any remaining missing values, and ensuring that the reviews were correctly loaded and cleaned. This step acted as a final validation to confirm that the data was ready for sentiment analysis.

By performing these preprocessing steps, the review data was prepared for accurate and efficient sentiment analysis, ensuring the reliability of the subsequent analysis and results.

**SENTIMENT ANALYSIS METHODOLOGY**

The sentiment analysis methodology employed in this project involved a combination of classical and modern natural language processing (NLP) techniques to assess the sentiment expressed in the product reviews. The methodology encompassed several key steps, including selecting appropriate sentiment analysis models, configuring the models, and implementing the analysis process.

**Model Selection:** Two primary sentiment analysis models were selected for this project: VADER (Valence Aware Dictionary and sEntiment Reasoner) and RoBERTa (Robustly Optimized BERT Pretraining Approach).

**VADER:** VADER is a lexicon and rule-based sentiment analysis tool specifically attuned to sentiments expressed in social media. It is efficient, requires no pre-training, and is effective in handling a wide range of text complexities and contexts. VADER produces four sentiment scores: positive, negative, neutral, and compound (an aggregated score representing the overall sentiment).

**RoBERTa:** RoBERTa is a transformer-based model that builds on BERT (Bidirectional Encoder Representations from Transformers) by optimizing the training methodology. It excels in understanding context and nuances in text, making it highly effective for sentiment analysis. RoBERTa provides sentiment classifications along with confidence scores for positive, neutral, and negative sentiments.

**Configuration and Model Integration:** Configuring these models involved setting up the necessary libraries and ensuring the models were properly initialized for analysis.

**VADER Configuration:** The VADER model was configured using the `nltk` library, which provides easy access to the VADER sentiment analyser. No additional training was required, allowing for immediate application to the text data.

**RoBERTa Configuration:** The RoBERTa model was accessed through the `transformers` library provided by Hugging Face. This involved loading the pre-trained model and tokenizer to process the text data. The model's ability to handle fine-tuning for specific tasks allowed for more precise sentiment analysis tailored to the nuances of product reviews.

**Sentiment Analysis Process**

1**. Text Processing:** Each review was tokenized and processed to prepare it for sentiment analysis. For VADER, this involved simply passing the text to the analyser. For RoBERTa, the text was tokenized using the model's tokenizer, converting it into the appropriate input format.

2. **Sentiment Scoring:**

**VADER:** The processed text was analysed to produce the four sentiment scores (positive, negative, neutral, and compound). The compound score was particularly useful for summarizing the overall sentiment of each review.

**RoBERTa:** The text was fed into the RoBERTa model to obtain sentiment scores. The model output was processed to derive the confidence scores for each sentiment category.

3. **Result Integration:** The sentiment scores from both models were integrated into the dataset. This involved mapping the sentiment scores back to the corresponding reviews, allowing for a comprehensive analysis combining insights from both models.

**Handling Ambiguities and Edge Cases**

To ensure robustness, the methodology included handling ambiguities and edge cases:

**Retry Mechanism:** For scenarios where the model faced issues like rate limiting or text processing errors, a retry mechanism was implemented with exponential backoff to ensure reliable results.

**Invalid Reviews:** Reviews that were empty or invalid were identified and skipped to maintain data integrity.

**Final Sentiment Calculation**

The final sentiment calculation involved aggregating the results to derive meaningful insights. This included calculating overall sentiment distributions, correlating sentiment scores with review ratings, and identifying trends or patterns in the sentiment data.

By combining the strengths of VADER and RoBERTa, this methodology provided a comprehensive and nuanced understanding of the sentiments expressed in the product reviews. The dual-model approach leveraged the efficiency of rule-based analysis and the depth of transformer-based models, resulting in a robust sentiment analysis framework.

**IMPLEMENTATION**

The implementation of the sentiment analysis involved a systematic approach, leveraging both VADER and RoBERTa models. This section outlines the key steps taken to implement the analysis, from data preparation to final sentiment scoring.

**Data Preparation**

The first step in the implementation process was to prepare the review data. This included loading the CSV file containing the reviews, handling missing values, and performing basic data cleaning. The data was then exported to a text file to facilitate easy processing by the sentiment analysis models.

**Model Configuration**

Two primary sentiment analysis models were configured for this project: VADER and RoBERTa. Each model required specific setup and configuration steps:

**VADER Configuration:** The VADER model was configured using the `nltk` library. This involved importing the library and initializing the sentiment analyzer. VADER's pre-built lexicon and rule-based approach required no additional training, allowing for immediate application to the review data.

**RoBERTa Configuration:** The RoBERTa model, accessed via the `transformers` library, required loading the pre-trained model and tokenizer. This step involved specifying the model (`cardiffnlp/twitter-roberta-base-sentiment-latest`) and ensuring the necessary dependencies were installed. The tokenizer was used to process the text data into a format suitable for the RoBERTa model.

**Sentiment Analysis Execution**

1**. Text Tokenization and Processing:** Each review was tokenized and processed to prepare it for sentiment analysis. For VADER, the text was directly passed to the analyser. For RoBERTa, the tokenizer converted the text into the required input format, producing tokenized sequences suitable for model inference.

2. **Sentiment Scoring:**

**VADER:** The VADER analyser produced four sentiment scores: positive, negative, neutral, and compound. These scores were directly extracted from the analyser's output.

**RoBERTa:** The tokenized text was fed into the RoBERTa model to obtain sentiment scores. The model output provided confidence scores for each sentiment category (positive, neutral, negative), which were processed to derive the final sentiment scores.

3. **Error Handling and Retries:** To ensure robustness, a retry mechanism was implemented to handle errors such as rate limiting and processing issues. This involved exponential backoff to manage retries efficiently, ensuring reliable results even in the face of occasional errors.

**Integration of Results**

The sentiment scores from both VADER and RoBERTa were integrated into the dataset. This involved mapping the sentiment scores back to the corresponding reviews, resulting in a comprehensive dataset containing both sentiment and review data. The integration process was carefully managed to maintain data integrity and ensure accurate mapping of scores.

**Sentiment Score Aggregation**

The final step in the implementation was to aggregate the sentiment scores to derive meaningful insights. This included calculating overall sentiment distributions, correlating sentiment scores with review ratings, and identifying trends or patterns in the sentiment data. The aggregation process involved:

**Calculating Percentages:** Determining the proportion of positive, neutral, and negative sentiments in the dataset.

**Summarizing Sentiments:** Creating summary statistics to capture the overall sentiment landscape of the reviews.

**Visualizing Results:** Generating visual representations of the sentiment analysis results to facilitate easy interpretation and communication of findings.

**Saving and Exporting Results**

The final dataset, including both the original reviews and the sentiment scores, was saved and exported for further analysis and reporting. This step ensured that the processed data was available for subsequent stages of the project, including result discussion and report generation.

**RESULTS AND DISCUSSION**

The sentiment analysis of the product reviews provided valuable insights into customer perceptions and highlighted key patterns and trends. This section discusses the results obtained from the analysis and their implications.

**Overall Sentiment Distribution**

The analysis revealed the overall sentiment distribution among the product reviews. The sentiment scores from both VADER and RoBERTa models were aggregated to identify the proportion of positive, neutral, and negative sentiments.

**Positive Sentiment:** A significant portion of the reviews expressed positive sentiments, indicating general satisfaction with the product. This was reflected in both VADER and RoBERTa scores.

**Neutral Sentiment:** A moderate number of reviews were classified as neutral, suggesting that while some customers were neither particularly satisfied nor dissatisfied, they found the product to be adequate.

**Negative Sentiment:** A smaller yet notable portion of the reviews indicated negative sentiments, highlighting areas where customers experienced dissatisfaction or issues.

**Correlation with Review Ratings**

The sentiment scores were correlated with the review ratings to understand how sentiment aligned with the star ratings provided by customers.

**High Ratings (4-5 stars):** Reviews with high ratings predominantly exhibited positive sentiment scores, corroborating the high satisfaction levels indicated by the star ratings.

**Medium Ratings (2-3 stars):** Reviews with medium ratings showed a mix of positive, neutral, and negative sentiments. This diversity in sentiment scores suggests that customers had mixed feelings about the product, recognizing both strengths and weaknesses.

**Low Ratings (1 star):** Reviews with low ratings were strongly associated with negative sentiment scores, reflecting clear dissatisfaction and highlighting specific issues faced by customers.

**Identified Trends and Patterns**

**Common Positive Aspects:** Customers frequently praised the product's value for money, speed, and performance. These positive aspects were consistently highlighted in the sentiment analysis, indicating key strengths of the product.

**Common Negative Aspects:** Negative reviews often mentioned issues related to heating problems, poor performance under certain conditions, and unmet expectations. These recurring themes point to areas where improvements could be made to enhance customer satisfaction.

**Neutral Feedback:** Neutral feedback often centered around the product meeting basic expectations without exceeding them. These reviews provided a balanced view, highlighting both satisfactory and average aspects of the product.

**Visual Representation**

**Bar Charts:** Bar charts were used to depict the distribution of sentiment scores across different star ratings, highlighting the correlation between sentiment and customer ratings.

**Sentiment Breakdown:** Detailed breakdowns of positive, neutral, and negative sentiments were presented to show the proportion of each sentiment category within the dataset.

**Trend Analysis:** Trends and patterns were visualized to identify common themes in positive and negative feedback, offering actionable insights for product improvement.

**Implications and Recommendations**

**Enhancing Positive Aspects:** By understanding what customers appreciate about the product, these aspects can be further enhanced and highlighted in marketing efforts.

**Addressing Negative Feedback:** Identifying common issues allows for targeted improvements, potentially reducing negative feedback and increasing overall customer satisfaction.

**Balanced View:** Neutral feedback provides a balanced perspective, helping to identify areas that meet expectations but have room for enhancement.

In conclusion, the sentiment analysis provided a comprehensive view of customer feedback, revealing valuable insights into the product's strengths and areas for improvement. By leveraging these insights, strategies can be developed to enhance the product and better meet customer needs.

**CONCLUSION**

The sentiment analysis of the product reviews has provided a deep and comprehensive understanding of customer perceptions and sentiments. By employing both VADER and RoBERTa models, we were able to capture a wide spectrum of emotions and opinions expressed in the reviews.

1. **Positive Sentiment Dominance:** The majority of reviews exhibited positive sentiments, indicating a high level of customer satisfaction. Customers frequently praised the product for its value for money, speed, and overall performance.

2. **Correlation with Ratings:** There was a strong alignment between sentiment scores and star ratings. Higher-rated reviews (4-5 stars) correlated with positive sentiment scores, while lower-rated reviews (1-2 stars) were associated with negative sentiments. This correlation validates the effectiveness of sentiment analysis in accurately reflecting customer satisfaction levels.

3. **Identified Areas for Improvement:** Negative reviews highlighted specific issues, such as heating problems and performance under certain conditions. These recurring themes offer valuable insights into areas where the product could be improved to better meet customer expectations.

4.**Balanced Feedback:** Neutral reviews provided a balanced perspective, indicating that while the product meets basic expectations, there are areas where enhancements could be made to exceed customer satisfaction.

The insights gained from this sentiment analysis have significant implications for product development and customer service strategies. By focusing on enhancing the positive aspects that customers appreciate and addressing the common issues highlighted in negative reviews, the product can be refined to better meet customer needs and expectations.

Moreover, the use of sentiment analysis as a tool for continuous feedback and improvement can be integrated into regular product review processes. This approach allows for ongoing monitoring of customer sentiments, providing real-time insights that can inform agile responses to emerging issues and evolving customer preferences.

In summary, the sentiment analysis has successfully uncovered valuable insights into customer sentiments, providing a clear picture of the product's strengths and areas for improvement. By leveraging these insights, strategies can be developed to enhance product quality, increase customer satisfaction, and ultimately drive business success. This analysis underscores the importance of listening to customer feedback and using advanced analytical tools to transform raw data into actionable insights.

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