Amazon Product Review Sentiment Analysis

Leveraging Social Media Analytics for Product Sentiment Insights

Course: Social Media Analytics

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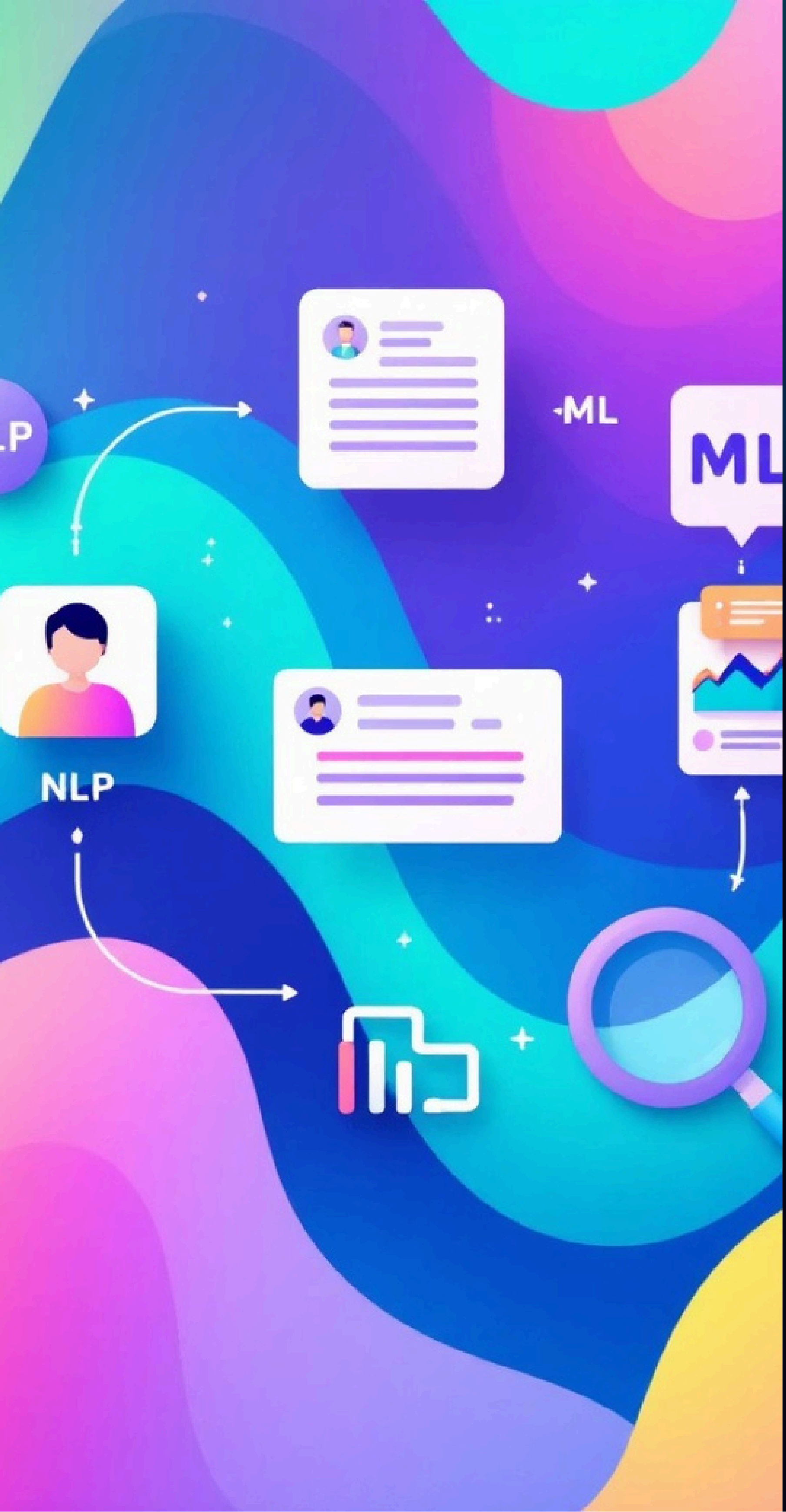


Introduction to Sentiment Analysis

Defining Sentiment Analysis

Utilising NaturalLanguage Processing(NLP)and Machine Learning (ML) to classify customer opinions into positive, negative, or neutral categories.

E-Commerce Significance

Productreviewsareahighlyauthenticsource of unfiltered customer feedback and perception.

Driving Business Value

Insightsgainedhelpidentifyproduct strengths, pinpoint weaknesses, understand satisfaction drivers, and refine marketing strategies.

Our Core Focus

AnalysingAmazonproduct reviews to reveal specific customer perceptions of smart devices, particularly Amazon Alexa products.

Why Amazon Product Reviews Matter

Global Reach: Amazon'sstatusas thelargest global e-commerce marketplace provides an unparalleled volume of data.

- Millions ofcustomers leave **unsolicited, authentic reviews** daily.
- These reviews offer a direct window into mass consumer sentiment.

Tangible Impact: Research consistently demonstrates the direct correlation between review sentiment and sales performance.

- Positive reviews actively drivesales growth.
- Negative reviews act as significant deterrents to purchases.

StrategicInsights: Proactive monitoring of Amazon reviews offers real-time strategic advantages.

- Immediatefeedbackon customerexpectations.
- Benchmarking against competitors' product perceptions.
- Early identification of emerging product issues or oppor tunities.

Use Case: Amazon Alexa Devices

AI Adoption Trends

Alexa-enableddevicesareamong the fastest-growing AI-based consumer products, making them a prime subject for sentiment analysis.

Common Praises

Reviews frequentlyhighlight ease of setup, superior sound quality, accurate voice command recognition, robust connectivity, and seamless smart home integration.

Key Criticisms

Negative feedback often centres on persistent connectivity failures, issues with command recognition, and concerns regarding device durability over time.

Strategic Relevance

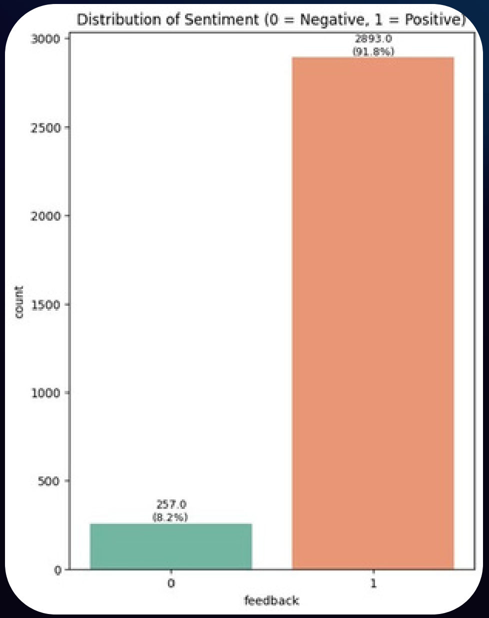
Analysing thesereviewsprovides vital insights into both evolving AI adoption and practical areas for product improvement, critical for both business and academic understanding.

Dataset Overview: Amazon Alexa Reviews

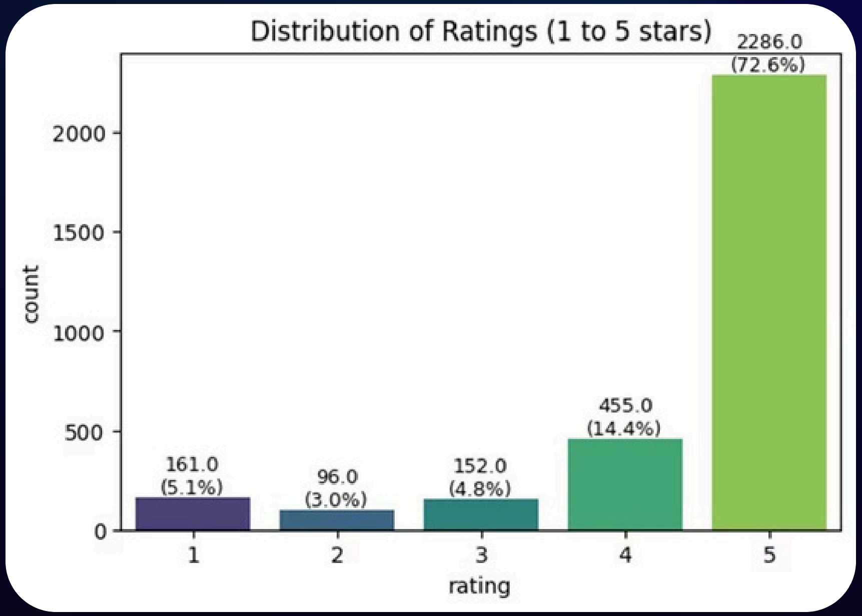
Source	Kaggle: *Amazon Alexa Reviews Dataset*
Size	3,150 customer reviews
Key Attributes	Rating (1-5 stars), Review Date, Variation (e.g., Echo Dot, Echo Plus), Verified Reviews (text), Feedback (Positive=1, Negative=0)
Average Rating	Approximately 4.4 out of 5, indicating an overall positive sentiment trend.
Sentiment Imbalance	Highly skewed with 90% positive reviews versus 10% negative, presenting a challenge for model training.
Review Length	Varied significantly, from concise declarations ("Love it!") to extensive, detailed complaints.

This rich dataset allows for comprehensive sentiment analysis, despite the inherent class imbalance, offering a nuanced view of customer satisfaction with Alexa devices.

Exploratory Data Analysis: Sentiment & Ratings



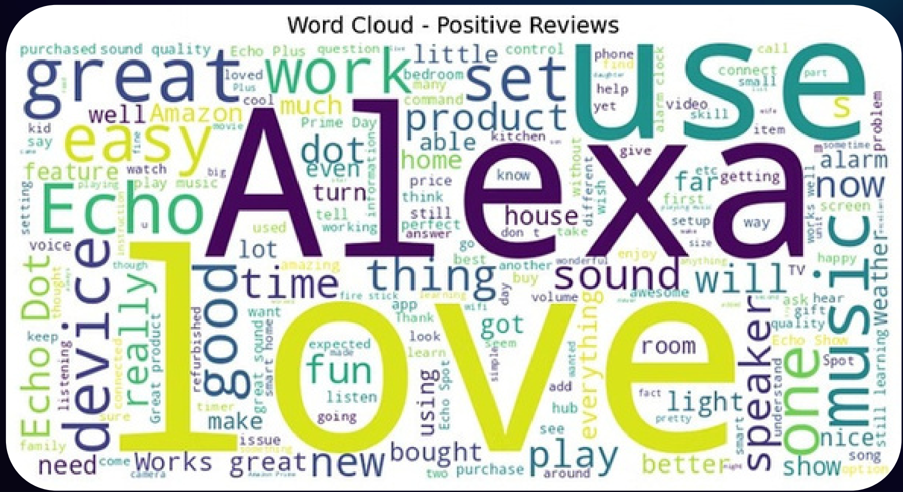
Sentiment Distribution

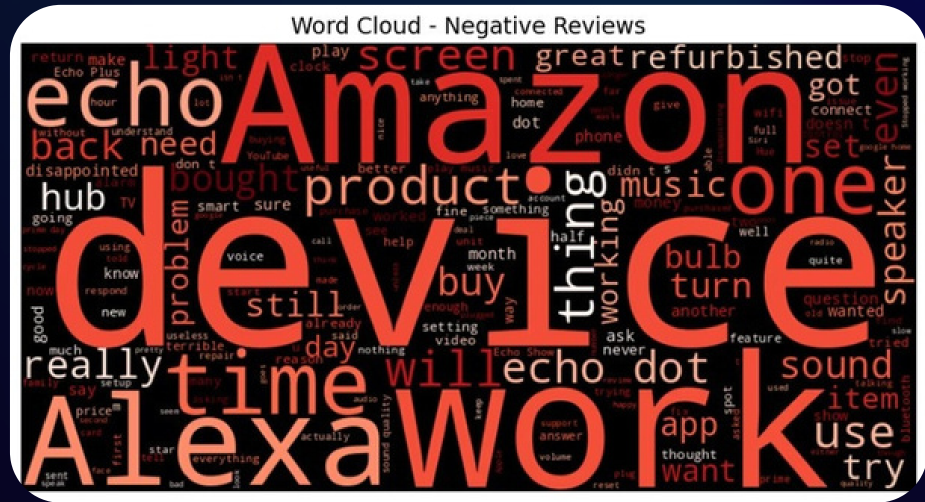


Rating Distribution

The analysis reveals strong customer approval for Alexa devices, with a dominant 92% positive sentiment. While negative reviews are fewer (8%), they are critical for identifying specific areas requiring attention, particularly with very few 1- and 2-star ratings.

Exploratory Data Analysis: Review Patterns





Positive Keywords

- Concise reviews frequently expressed broad satisfaction.
- Common terms: "love," "great," "easy," "music," "fun."

Negative Keywords

- Longer reviews often contained detailed grievances.
- Common terms: "problem," "issue," "return," "doesn't," "still."

Key Takeaway: Dissatisfied customers often provide more extensive feedback, offering invaluable deep-dive insights into product shortcomings and areas for improvement.

Model Implementation

Preprocessing Steps

- Tokenization:Breaking text into individual words or phrases.
- Stopword Removal: Eliminating common words (e.g., 'the', 'a') that add little meaning.

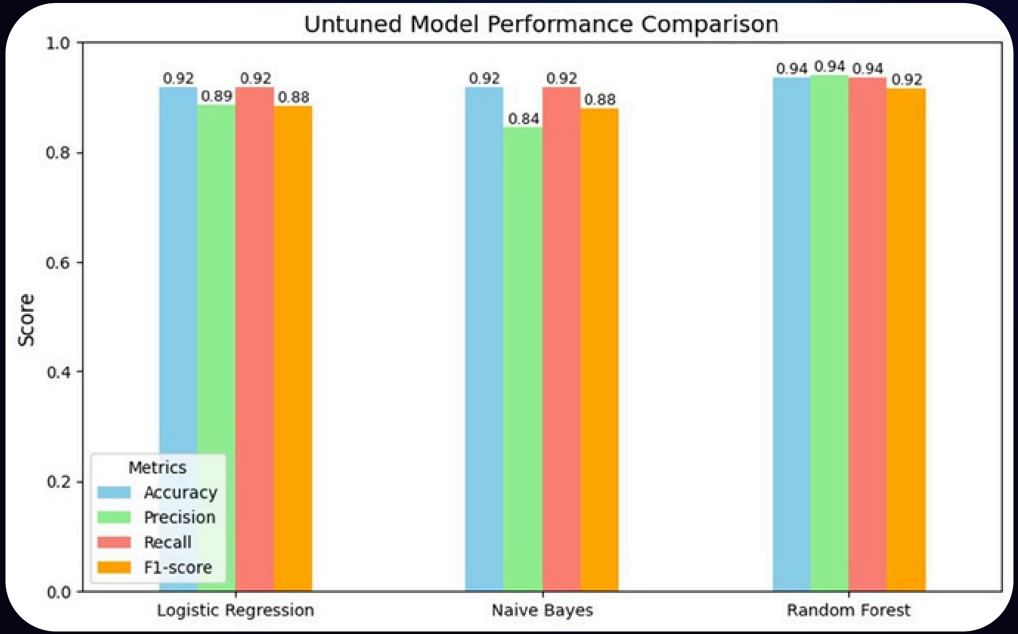
Models Utilised

- LogisticRegression: A linear, interpretable model, serving as a robust baseline.
- Naïve Bayes: A probabilistic model particularly effective for text classification.
- Random Forest: An ensemble method capable of capturing complex, non-linear relationships.

Train-Test Split

An80-20ratiowasapplied to split the dataset, ensuring a fair and unbiased evaluation of model performance.

Untuned Model Performance

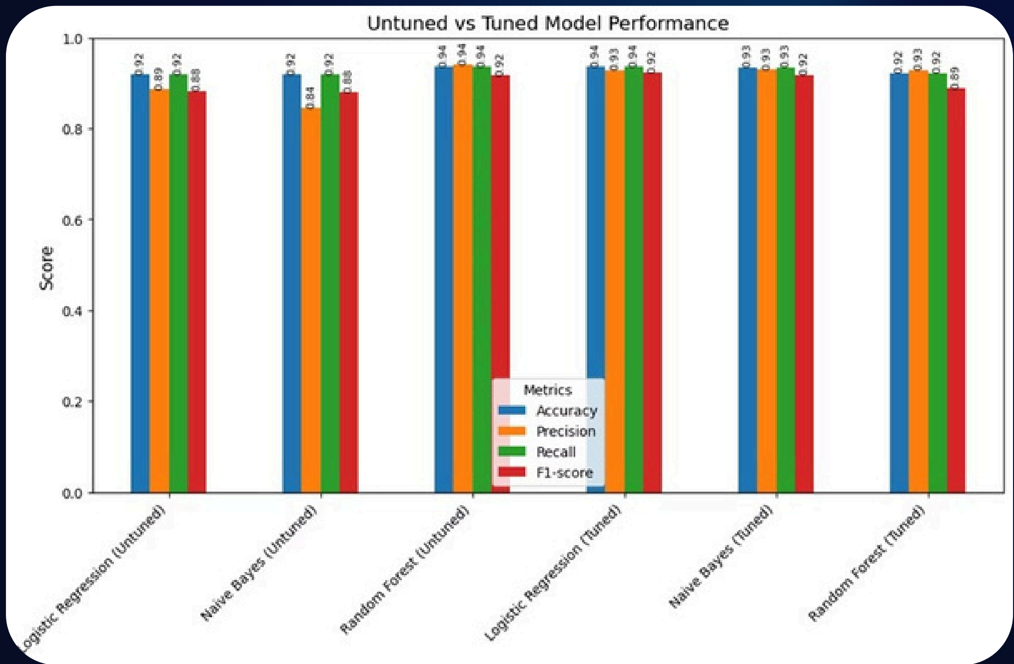


Accuracy of Untuned Models

Initial Observations

- All three baseline models demonstrated strong initial performance.
- Accuracies ranged from 92% to 94% on the test set.
- This robust performance suggests clear sentiment patterns within the review text, even without specific optimisation.
- Random Forest exhibited the highest accuracy straight out of the box, indicating its capacity to handle complex feature interactions effectively.

Tuned Model Performance: Optimising for Pr e cision



Accuracy Comparison: Untuned vs. Tuned Models

Hyperparameter Tuning via GridS e ar chCV

- Logistic Regression: Optimised regularization strength for improved generalization.
- Naïve Bayes: Adjusted smoothing factors to enhance probability estimations.
- Random Forest: Fine-tuned tree depth and number of estimators to prevent overfitting.

Key Takeaway

Logistic Regression emerged as the most reliable model, achieving **94% accuracy with the best recall balance** after tuning, making it ideal for robust sentiment classification.

Dashboard Highlights

- **ModelPerformance:** The dashboard vividly compares the accuracyof tuned versus untunedmodels, showcasing the improvements gained through optimization.
- **Confusion Matrix Insights:** It clearly displays the confusion matrix, highlighting excellent detection of positive sentiment while also revealing areas for improvement in identifying negative classifications.
- **Sentiment Distribution:** A compelling bar chart illustrates the predominant sentiment, with 92% positive reviews and 8% negative, providing a quick overview of customer satisfaction.
- **Key Word Frequencies:** The top 20 most frequent terms are presented, intelligently colored by their associated sentiment, offering immediate insights into common themes.
- **Enhanced Business Value:** By simplifying complex technical results into easily digestible visual insights, the dashboard empowers decision-makers with actionable information.

Business Insights & Recommendations

- **Customer Insights Positive Drivers:**User-friendly design,richmusicfeatures, and seamless smart home integration. **Negative Drivers:** Persistent connectivity issues, unreliable voice recognition, and concerns over refurbished unit quality.
- **Business Recommendations**
  - Enhance connectivity and improve firmware reliability.
  - Refine voice recognition capabilities and consider adding multilingual support.
  - Implement stricter quality control measures for refurbished devices.
  - Expand smart home device partnerships to foster ecosystem growth.
- **Strategic Implications**
  - Emphasize product strengths in marketing campaigns to attract new customers.
  - Utilize ongoing sentiment tracking to proactively identify and address potential product issues.
  - Leverage automated sentiment analysis to reduce dependence on expensive traditional surveys.

Conclusion

- Sentiment analysis servesas a **powerful decision-making tool**, especially within the e-commerce sector.
- While Alexa reviews demonstrate an overwhelming **92% positive sentiment**, the critical insights derived from negative feedback are invaluable for targeted improvements.
- The Logistic Regression model proved to be the most effective, achieving a robust **94% accuracy** in sentiment classification.
- **Business Impact:** This analysis enables the **continuous monitoring of customer sentiment**, fostering proactive product enhancements and building stronger customer trust.
- **Academic Impact:** The project successfully illustrates the significant potential of integrating **text mining, machine learning, and business analytics** for actionable insights.

Thank You!

We appreciate your time and attention to our analysis.

Questions & Discussion