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CUSTOMERS HAVE FEELINGS... AND THEY LEFT THEM ON *AMAZON!*

BUSINESS CASE

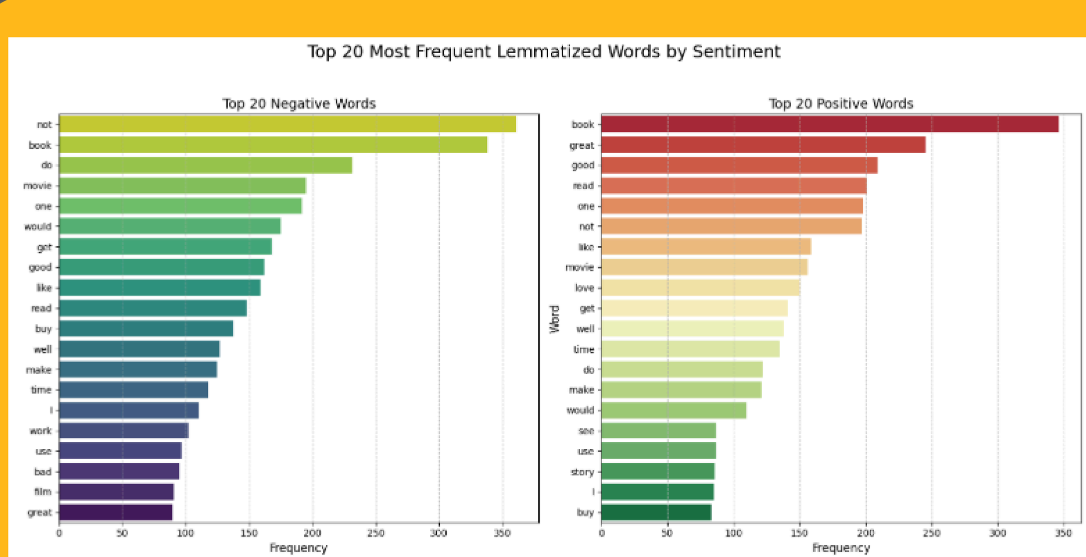
Businesses receive thousands of customer reviews daily, but without automated analysis, valuable insights about product performance and customer satisfaction remain buried in text. Sentiment analysis enables companies to systematically detect dissatisfaction, highlight what customers value most, and uncover recurring issues that impact sales and brand reputation. By transforming unstructured reviews into actionable intelligence, organizations can make faster, data-driven decisions about product improvements, marketing strategies, and customer support priorities.

OBJECTIVE

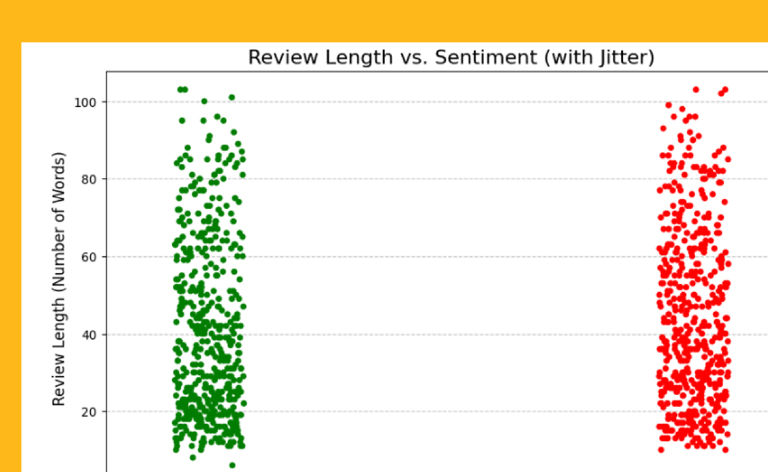
To extract actionable insights from customer reviews and build a sentiment classification model that reveals key drivers of satisfaction and dissatisfaction

METHODOLOGY

Data was cleaned, lemmatized, and transformed using TF-IDF. A Logistic Regression classifier was trained on labeled sentiment data. Additional analyses included N-grams, semantic search, PCA visualization, word frequency analysis, and word clouds.



Frequent-word patterns show clear differences in how customers express sentiment. Negative reviews are dominated by strong modifiers like "not," "bad," "poor," and action words linked to complaints such as "return," "waste," and "do." Positive reviews center on appreciative terms such as "great," "good," "love," and "excellent," often paired with product-specific words like "book" and "movie." These contrasting vocabularies highlight what customers consistently praise versus what triggers dissatisfaction.



The jitter plot shows heavy overlap between positive and negative review lengths, with no clear separation between the two groups. This confirms that customers write both positive and negative reviews at similar lengths, and review length offers no meaningful predictive signal for sentiment.

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Accuracy: 0.7900
Precision: 0.7940
Recall: 0.7900
F1-Score: 0.7891
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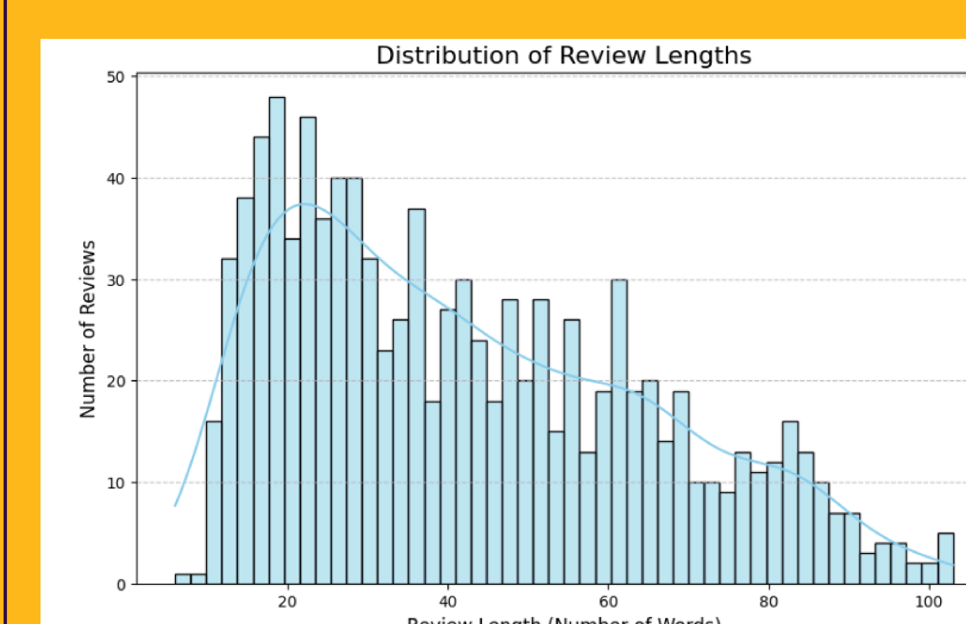
Classification Report:

	precision	recall	f1-score	support
1	0.76	0.85	0.80	101
2	0.83	0.73	0.77	99
accuracy			0.79	200
macro avg	0.79	0.79	0.79	200
weighted avg	0.79	0.79	0.79	200

The model achieved 79% accuracy with balanced precision and recall. It detects negative reviews strongly (recall 0.85) but is more selective with positive ones (recall 0.73). Positive predictions are highly precise (0.83), while negative predictions are more inclusive, showing the model prioritizes catching dissatisfaction, useful for customer experience monitoring.



Review lengths follow a right-skewed pattern, with most customers writing concise reviews around 20–40 words and fewer producing long, detailed feedback, showing that brief comments dominate customer communication.

IMPLICATIONS

The findings show that the model can reliably surface dissatisfaction, helping businesses quickly identify and respond to negative experiences. Clear sentiment drivers and recurring phrases reveal what customers consistently value or criticize, guiding product improvements and sharper marketing. Semantic search adds the ability to track specific issues in real time, making the system useful for large-scale review monitoring and customer experience optimization.

LIMITATIONS

The model's TF-IDF approach cannot fully capture nuance, sarcasm, or deeper context, and noise or mislabeling in user-generated reviews may affect accuracy. Sentiment patterns also do not separate cleanly in reduced dimensions, limiting interpretability. The dataset sample and domain specificity reduce generalizability, meaning performance may decline on different product categories or larger, more diverse review sets.

CONCLUSIONS

This study demonstrates that sentiment analysis can extract meaningful patterns from Amazon customer reviews, revealing the linguistic signals that shape satisfaction and dissatisfaction. The model performs reliably, identifying negative feedback with high sensitivity while capturing the key themes that drive positive experiences. Although limited by dataset scope and the simplicity of TF-IDF features, the results offer actionable insights for improving products, refining messaging, and enhancing customer experience strategies.