GROUP 11

Product Review Classification

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Project Overview

Objective
classifying product reviews using pretrained HuggingFace models

Focus
briefly showcasing the models and their results

Key Question
"What practical applications can these results have?"

Dataset Overview

This is a large-scale Amazon Reviews dataset, collected in 2023 by <u>McAuley Lab</u>, and includes features such as:

1. User Reviews (ratings, text, helpfulness votes, etc.);

2. Item Metadata (descriptions, price, raw image, etc.);

3. Links (user-item / bought together graphs).

DATA PREPROCESSING

FOCUS ON VIDEO GAME REVIEWS

abc

LOWERCASING

WORD

REMOVING STOPWORDS

REMOVING SPECIAL CHARACTERS

Model 1:
## LiYuan/amazon-review-sentiment-analysis

Our Goal

predicting 1-5 star rating based on review text

Results

Accuracy: 69.07%

The model excels at identifying 5-star reviews, with around 1700 correct predictions. It struggles with nuances, often misclassifying 3-star and 4-star reviews, leading to approximately 300 and 400 misclassifications in these categories. Despite these challenges, the overall accuracy and strong performance in identifying positive sentiment shows the model's potential for practical use. With more time, we would be able to address the misclassifications and achieve higher accuracy across all star rating categories.

Model 1_confusion matrix

Confusion Matrix
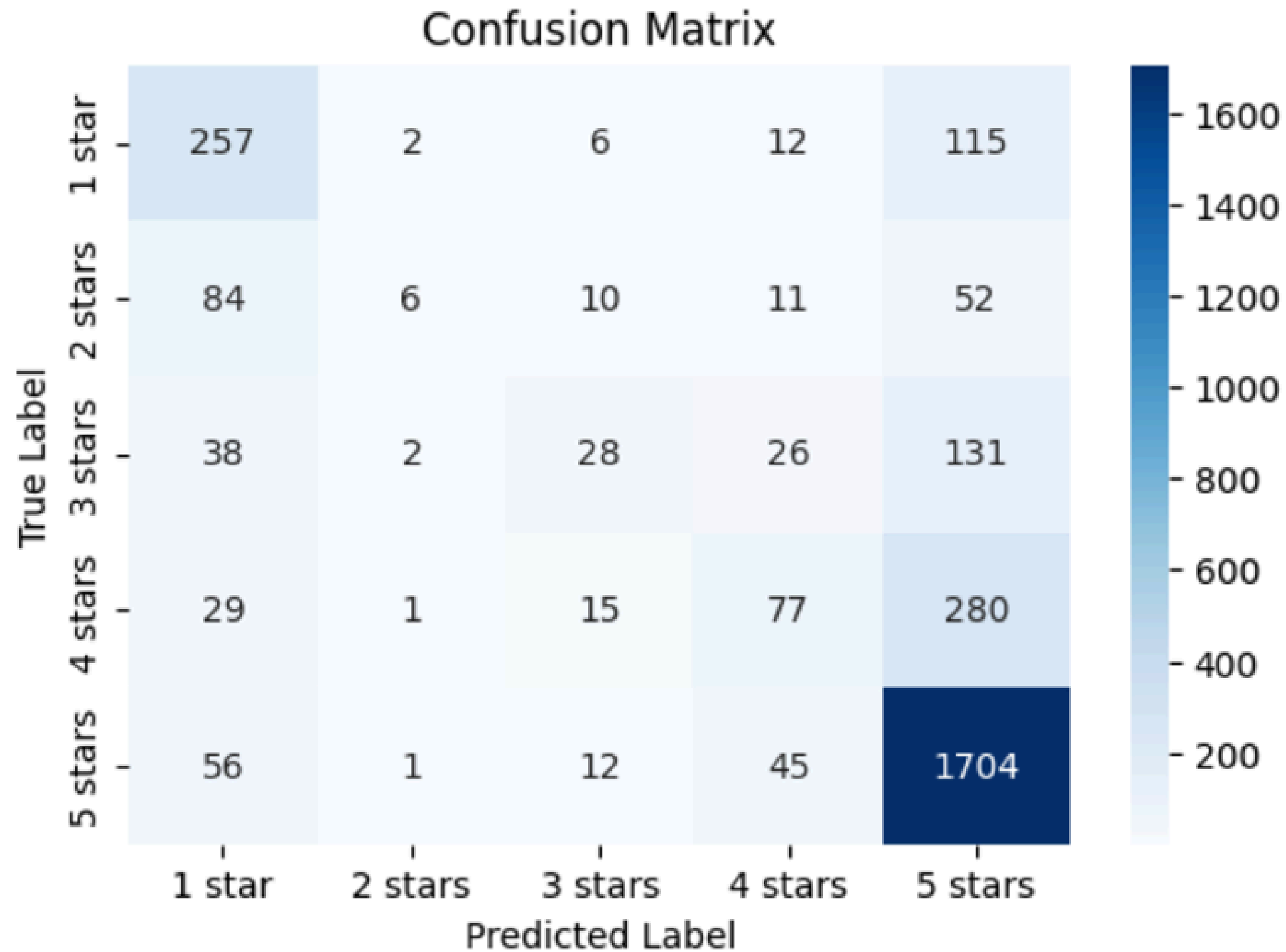
Model 2:
distilbert/distilroberta-base

Our Goal

**categorizing review text into "negative", "neutral" and "positive"**

Results

Accuracy: 37.90%

The model performs best with positive reviews, correctly classifying 622. For negative reviews, only 153 are correctly identified, while 64 are misclassified as positive and 338 as neutral. The model struggles significantly with neutral reviews, correctly classifying just 362, while 207 are misclassified as positive and 58 as negative.

These results suggest that the model has a bias toward predicting positive and neutral sentiments while struggling to correctly identify negative and neutral reviews. This suggests a need for further fine-tuning on the dataset and potentially better handling of class imbalances to improve performance.

Model 2_confusion matrix
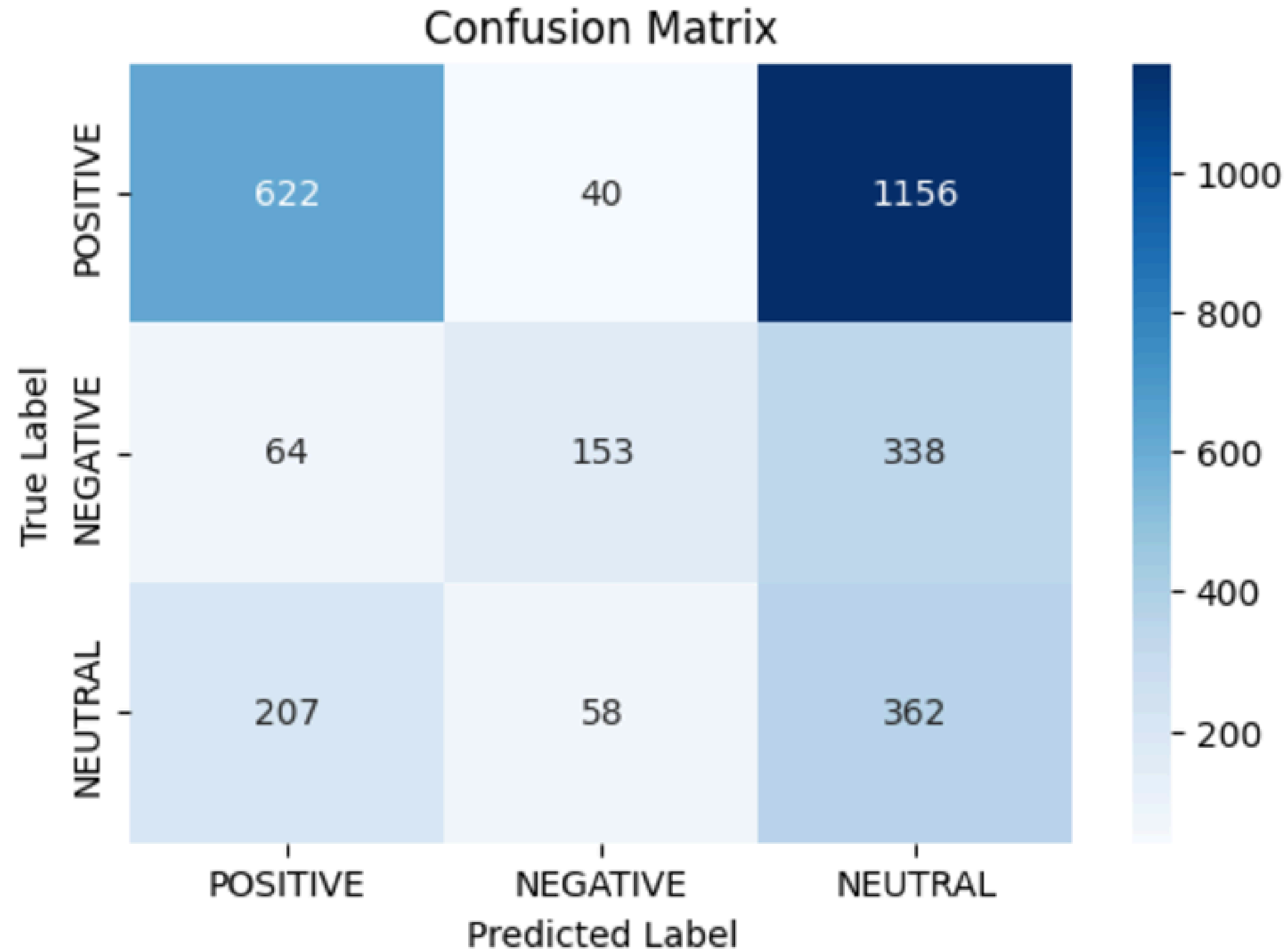
REAL-WORLD APPLICATIONS

Star Rating

★★★★☆

- **Enhanced Product Recommendations:** Predict star ratings for unrated products to improve personalized suggestions.

- **Seller Insights:** Identify trends in product performance to guide improvements or promotions.

- **Automated Review Summarization:** Group reviews by predicted star ratings for quick consumer insights.

- **Customer Satisfaction Monitoring:** Detect shifts in overall sentiment for a product or category.

- **Prioritized Feedback Management:** Flag negative reviews for faster responses by customer service teams.

- **Market Trends Analysis:** Aggregate sentiment data to evaluate reception of product launches or updates.

Sentiment Analysis

CONCLUSION

Model Performance and Insights
The LiYuan model demonstrated promising accuracy (~70%) for predicting star ratings, making it suitable for applications like recommendations and review summaries. On the other hand, distilroBERTa's lower accuracy (~40%) highlighted the need for fine-tuning or more domain-specific models for sentiment classification.

Practical Applications
Despite challenges, these models can enhance customer experience by automating insights, prioritizing feedback, and monitoring product trends. After further improvements, they could streamline review analysis in e-commerce.

References

Hugging Face Models

LiYuan/amazon-review-sentiment-analysis
    https://huggingface.co/LiYuan/amazon-review-sentiment-analysis

distilbert/distilroberta-base
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other references

OpenAI. (2024). ChatGPT (Nov 26 version) [Large language model].
    https://chat.openai.com/chat

Google. (2024). Gemini AI (Nov 26 version) [Large language model].
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Thank you for your attention