An Adaptive Model for Catalyzing Digital Marketing Using Machine Learning

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Abstract

In today's digital era, the vast amount of unstructured data generated daily from different data sources like social media, e-commerce platforms, emails, blogs, and other online sources has made sentiment analysis a critical tool for businesses. This paper aims to analyze Amazon customer reviews using a three-tier approach: (1) data preprocessing, (2) statistical feature selection to identify key variables, and (3) classification with machine learning algorithms—Random Forest, Naïve Bayes, and SVM. The classifiers are evaluated using performance metrics such as accuracy, precision, F-measure, true positive rate, and false negative rate. A comparative analysis reveals their strengths and limitations, providing actionable insights for optimizing sentiment analysis. This paper enhances sentiment analysis through structured processing of unstructured reviews, providing businesses with actionable insights involving stacking ensemble combining Naïve Bayes, Gradient Boosting, Neural Networks under an XGBoost for sentiment analysis to drive data-based decisions and improve customer satisfaction.

Keywords: Sentiment Analysis, Machine Learning, Customer Reviews, Supervised Learning, Digital Marketing.

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نموذج تكيفي لتحفيز التسويق الرقمي بإستخدام التعلم الآلي

الملخص

في العصر الرقمي الحالي، أصبحت الكميات الهائلة من البيانات غير المهيكلة التي يتم توليدها يوميًا من مصادر مختلفة مثل وسائل التواصل الاجتماعي ومنصات التجارة الإلكترونية والبريد الإلكتروني والمدونات وغيرها من المصادر عبر الإنترنت، جعلت تحليل المشاعر أداة حاسمة للشركات. يهدف هذا البحث إلى تحليل تقييمات العملاء على موقع أمازون باستخدام منهجية ثلاثية المستويات: (1) معالجة البيانات المبدئية، (2) اختيار السمات الإحصائية لتحديد المتغيرات المؤثرة، و(3) التصنيف باستخدام خوارزميات التعلم الآلي مثل غابة القرارات (Random Forest) والتصنيف الساذج (Naïve Bayes) وآلات ناقلات الدعم (SVM). يتم تقييم أداء هذه المصنفات باستخدام مقاييس الأداء مثل الدقة والضبط (precision) ومقياس F ومعدل الإيجابيات الحقيقية ومعدل السلبيات الكاذبة. استخدمت الدراسة خوارزميات تعلم مُعمق متنوعة غابة القرارات العشوائية، التصنيف الساذج، آلات ناقلات الدعم SVM، الشبكات العصبونية، تعزيز التدرج بهدف تطوير نموذج تراكمي (Stacking Ensemble)لتحليل مشاعر العملاء في تقييمات إلكترونيات أمازون. بما يمكّن الشركات من اتخاذ قرارات مبنية على البيانات، وتحقيق مستويات أعلى من رضا العملاء، وتعزيز قدرتها التنافسية في الأسواق.

الكلمات المفتاحية: تحليل المشاعر، التعلم الآلي، تقييمات العملاء، التعلم الموجّه، التسويق الرقمي، خوارزميات

1. INTRODUCTION

Machine learning-powered adaptive models have revolutionized digital marketing, providing a sophisticated approach to harnessing real-time data and consumer insights. These models integrate advanced analytics to process massive amounts of information through customer reviews and product feedback, enabling businesses to formulate strategies and respond dynamically to market changes. In this ever-evolving field, adaptability is essential, and machine learning is proving invaluable by identifying changing patterns in consumer behavior and improving marketing decisions by leveraging customer feedback [4].

These models enable businesses to make immediate product adjustments, improving engagement in competitive landscapes. Often termed adaptive analytics intelligent marketing [3], this approach allows instant response to market fluctuations. This rapid adaptability is essential to maintaining a competitive advantage, as organizations can quickly seize opportunities or pivot to mitigate potential challenges particularly granular risks like software defects or privacy concerns identified through aspect-level sentiment monitoring [14]. Digital marketers gain a comprehensive view by integrating multi-channel data [9], enabling hyper-personalized interactions and real-time campaign calibration [10].

Digital marketers gain a comprehensive view of customer interactions by integrating data from multiple channels, such as e-commerce sites. This integration enables highly personalized and contextually relevant interactions with their audiences, ensuring that marketing efforts align closely with consumer needs and preferences [9]. The ability to analyze and respond to data in real-time allows for more precise targeting, improved customer satisfaction, and enhanced brand loyalty [10].

Adaptive digital marketing analytics can be deployed in two complementary modes [6]. In the on-demand approach, insights are generated whenever analysts or decision-makers require them; in the continuous approach, insights flow in automatically as new data arrive. Continuous analytics, for example, empowers marketers to monitor and adjust content performance in real time, using live metrics to fine-tune campaigns as they unfold. This capability for immediate feedback not only enriches strategic decision-making but also catalyzes the execution of more agile, effective digital marketing initiatives—ultimately driving competitive success in today's dynamic online environment [16]. Building on this foundation of adaptive intelligence, we now turn our attention to one of the most data-intensive domains in digital marketing: the analysis of consumer sentiment in e-commerce [19].

To address these needs, this study introduces a scalable sentiment-classification pipeline for roughly 35,000 Amazon electronics reviews. Beginning with pool-based active learning to minimize annotation effort, it proceeds through systematic preprocessing (tokenization, normalization, POS tagging, lemmatization), multi-level feature extraction (Bag-of-Words, TF-IDF, optional embeddings), and the training of diverse supervised models (SVM, k-NN, gradient boosting, neural networks, logistic regression) to provide stacking ensemble combining Naïve Bayes, Gradient Boosting, Neural Networks under an XGBoost meta-learner for sentiment analysis. Performance is then rigorously evaluated using accuracy, precision, recall, and F_1-score to ensure robust handling of class imbalance. The following section unpacks each stage of this methodology in detail.

2. RELATED WORKS

Recent years have witnessed a resurgence of interest in classical machine learning classifiers—particularly Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and ensemble methods—for large-scale e-commerce sentiment analysis.

2.1 Advancements in Classical Machine Learning Approaches

Recent research has demonstrated significant improvements in sentiment analysis through enhanced feature engineering and metadata integration. Daza et al. [5] pioneered the augmentation of traditional Bag-of-Words and TF-IDF representations with domain-specific lexicons for Amazon electronics reviews, achieving a 3-5% improvement in F_1-score. Their work further established that incorporating non-textual metadata—including star ratings, timestamps, and reviewer history—substantially enhances sentiment prediction robustness, particularly when linguistic signals alone prove ambiguous. Building on this foundation, Akter et al. [1] demonstrated that hyperparameter-tuned Support Vector Machines (SVMs) enriched with metadata features like review length and product category can boost F_1-scores by up to 7% compared to untuned models. Complementing these findings, Tabany et al. [18] conducted a comprehensive bibliometric analysis of 2018-2024 studies, revealing that hybrid pipelines combining SVM with shallow neural encoders consistently outperformed pure deep-learning baselines in both accuracy and training efficiency. Their systematic review of pool-based active learning schemes additionally confirmed that uncertainty sampling reduces annotation requirements by up to 60% without compromising model accuracy.

2.2 Transformer Architectures and Efficiency Innovations

The advent of transformer-based models has revolutionized sentiment analysis by automating feature extraction and capturing long-range dependencies. Suresh et al. [17] achieved breakthrough performance by fine-tuning BERT on a heterogeneous corpus of 50,000 Amazon electronics reviews, attaining 94.2% accuracy and an AUC-ROC of 0.97—surpassing LSTM and CNN baselines by over 8 percentage points. To address computational constraints inherent in transformer architectures, Liu et al. [7] developed a knowledge distillation approach that compresses BERT into "DistilSent," a 50% smaller model retaining 96% of full-model performance while halving inference time. Further efficiency gains were realized by Zhang et al. [12], who introduced lightweight transformer variants ("Electro BERT-Lite" and "Tiny BERT-E") reducing parameter counts by up to 70% with minimal accuracy degradation. Liu et al. [7] additionally demonstrated that combining active learning with synthetic data augmentation via masked language-model paraphrasing reduces labeling requirements by 20% while maintaining performance levels.

2.3 Multimodal and Semi-Supervised Frameworks

Integration of multimodal data sources has emerged as a critical pathway for enhancing sentiment analysis precision. Zheng et al. [19] developed a multimodal neural network that jointly processes TF-IDF vectors and user-level behavioral embeddings, yielding a 5% recall improvement over text-only BERT models. Similarly, Daza et al. [5] reported that appending temporal features (e.g., review recency) and product price tiers to standard text embeddings increased overall F_1-scores by 2.4%. Concurrently, semi-supervised approaches have addressed data scarcity challenges: Rehan et al. [17]

introduced a pseudo-labeling framework that leverages unlabeled data to achieve near-fully supervised accuracy using only 30% of annotated corpora, significantly reducing annotation costs while maintaining competitive performance.

Despite these advancements, three interrelated challenges remain. **First**, domain drift—the rapid introduction of new electronic products and jargon—continually erodes model accuracy unless continually retrained or adapted. **Second**, computational efficiency still limits real-time analysis at scale, especially for full-size transformer models. **Third**, the detection of deceptive or “fake” reviews requires more sophisticated approaches: although Dahiya et.al achieved promising results with SVM-based authenticity filters, integrating these checks into end-to-end pipelines remains underexplored [2]. Addressing these gaps will demand lightweight, adaptive architectures—potentially via continual learning or federated update schemes—and more holistic frameworks that unify sentiment scoring with deception detection and metadata analysis [4].

3. METHODOLOGY

This paper introduces a unified, end-to-end pipeline for classifying sentiment in nearly 35,000 Amazon electronics reviews, balancing the twin imperatives of accuracy and scalability. We begin by gathering raw review texts and star ratings from the electronics category, then use pool-based active learning to pinpoint and label only the most informative samples, dramatically cutting down manual annotation effort. Next, the data are cleaned, deduplicated, and converted into a balanced binary set of positive and negative labels.

The heart of our approach lies in a rich text-processing suite, tokenization, normalization, stop-word removal, POS tagging, and lemmatization, followed by feature extraction via Bag-of-Words, TF-IDF weighting, and optional word embeddings. Finally, we train a diverse ensemble of classifiers (SVM, k-NN, gradient boosting, neural networks, and logistic regression) and measure their performance with accuracy, precision, recall, and F_1-score. In the sections that follow, we unpack each of these stages in detail, demonstrating how they work together to deliver robust, scalable sentiment analysis for large-scale e-commerce data.

A. Data Acquisition

We began by compiling a dataset of roughly 35,000 Amazon reviews from the electronics category, spanning everything from cameras and laptops to smartphones and household gadgets. Each record includes the product's unique ID, the full text of the user's review, a star rating (1–5), the date the review was posted, and the reviewer's ID. To simplify the sentiment task, ratings of 1–3 were labeled as negative, while ratings of 4–5 were labeled as positive. As is common in e-commerce feedback, positive reviews far outnumbered negative ones, creating a pronounced class imbalance that would later influence our sampling and training strategies [13].

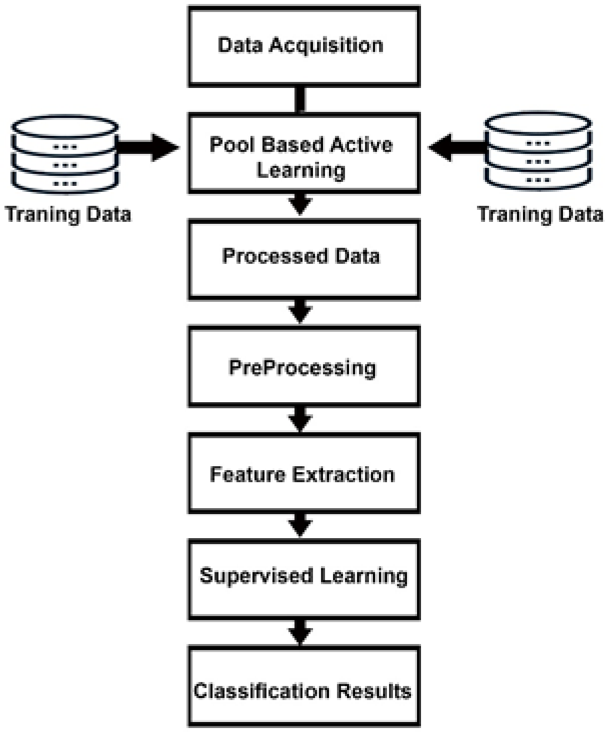


Figure 1. A proposed sentiment analysis model for Amazon product reviews

B. Pool-Based Active Learning

To reduce labeling effort and improve model performance, we used a pool-based active learning strategy. First, we trained an initial model on a small, randomly chosen set of labeled reviews. This model then scored the remaining unlabeled data, and we selected the reviews it was least confident about. These uncertain samples were manually labeled and added to the training set. We repeated this process, train, query, label, retrain, focusing on the most informative examples. This helped improve accuracy while requiring fewer labeled reviews [6].

C. Processed Data

Once labeled, the reviews were cleaned and reorganized for further analysis. We stripped out all non-textual metadata, product and user details, so that each record consisted solely of the review text plus its binary sentiment label. To address the skew toward positive feedback, we applied a combination of under sampling (randomly removing excess positive instances) and oversampling (replicating scarce negative instances), yielding a balanced dataset better suited for training [11].

D. Text Preprocessing

To prepare the text data for modeling, we applied several standard preprocessing steps. First, each review was tokenized, meaning it was broken into individual words or sub-word units. We then converted all text to lowercase and removed punctuation to eliminate case- or symbol-based distinctions (e.g., treating “Fast” and “fast” as the same word).

Next, we removed common stop words such as “the,” “and,” and “but,” as these typically carry little sentiment information. Each remaining word (token) was then tagged with its part of speech (e.g., noun, verb, adjective), since certain word types, especially adjectives and adverbs, are often strong indicators of sentiment.

Finally, we applied lemmatization, which reduces words to their base or dictionary forms. For instance, “running” and “ran” were reduced to “run,” and “better” to “good.” This step ensures that different word forms expressing the same meaning are treated consistently during analysis [9].

E. Feature Extraction

Next, we transformed the cleaned text into numerical features. We used two main methods: Bag of Words (which counts word occurrences) and TF-IDF (which gives more weight to rare and distinctive words across all reviews). For teams needing deeper understanding, we also offered the option to use pre-trained word embeddings (like Word2Vec or GloVe), which represent words based on their meanings and relationships with other words [9].

F. Supervised Learning

Using those extracted features, we trained a diverse ensemble of classifiers: Support Vector Machines (which find the optimal boundary between positive and negative examples), k-Nearest Neighbors (which labels a review based on its closest peers in feature space), gradient-boosted trees (which iteratively refine weak learners), feed-forward neural networks (which can uncover complex, non-linear patterns), and logistic regression (a fast, interpretable baseline). Each model was tuned via cross-validation to optimize its hyperparameters and guard against overfitting [8], [2], and [15].

G. Evaluation Measures

To We used a variety of indicators in addition to accuracy to determine success. We calculated the F_1 score (the harmonic mean of accuracy and recall), precision (the proportion of predicted positives that were correct), and recall (the percentage of true positives the model captured). True positives, false positives, incorrect negatives, and true negatives are the four matrixes of confusion counts that support these metrics. When taken as a whole, they paint a complex picture of how successfully each classifier differentiates positive sentiment from negative sentiment.

$$P = \frac{TP}{TP+FP}$$

Recall: Recall improves a classifier's sensitivity, or the proportion of positive data it yields. There are fewer false negatives when recall is higher. The ratio of properly classified an instance to all predicted instances is known as recall. This can be proved as.

$$R = \frac{TP}{TP+FN}$$

F-Measure: The weighted harmonic mean of accuracy and recall, or F-measure, is a single metric that is produced when precision and recall are mixed. It can be described as

$$F = \frac{2P.R}{P+R}$$

Accuracy: How frequently the classifier generates an accurate prediction is determined by performance. The amount of correct forecasts to total predictions is known as accurate.

$$Accuracy = \frac{Correct\ Prediction}{Total\ Data\ Points}$$

4. RESULTS AND DISCUSSION

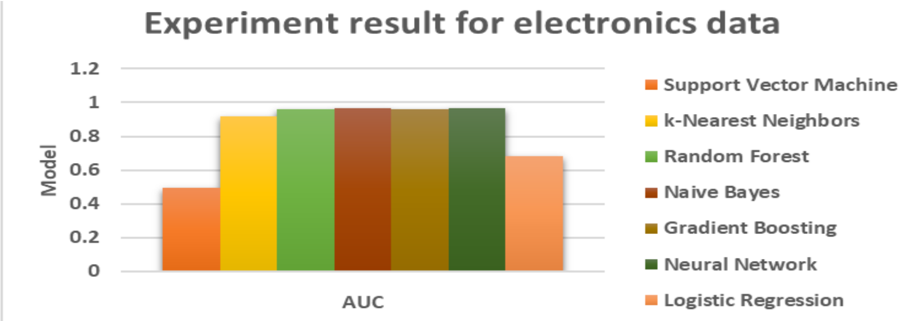
A diverse suite of classifiers are evaluated, Naïve Bayes, Support Vector Machine (SVM), Stochastic Gradient Descent

(SGD), Logistic Regression, Random Forest, and Decision Tree, on our balanced corpus of 35,000 Amazon electronics reviews. To ensure fair comparison and guard against overfitting, each model was assessed via k-fold cross-validation and scored on six key metrics: area under the ROC curve (AUC), classification accuracy (CA), F_1-score, precision, recall, and Matthews Correlation Coefficient (MCC).

Among the traditional learners, Naïve Bayes and Neural Networks emerged as strong performers, each achieving an AUC of 0.965 and overall accuracy of 94%. Gradient Boosting closely followed with an AUC of 0.962 and 93.1% accuracy, while Random Forests reached an AUC of 0.961 and 90.3% accuracy. In contrast, linear models such as SVM (AUC = 0.498, CA = 44.1%) and SGD lagged far behind, indicating that simple linear boundaries struggle to capture the complex language patterns in customer reviews.

Table 1. Experiment result for electronics data

Model	AUC	CA	F1	Precision	Recall	MCC
Support Vector Machine	0.498	0.441	0.486	0.691	0.441	0.023
k-Nearest Neighbors	0.921	0.883	0.885	0.886	0.883	0.643
Random Forest	0.961	0.903	0.902	0.901	0.903	0.691
Naive Bayes	0.965	0.94	0.943	0.953	0.94	0.841
Gradient Boosting	0.962	0.931	0.934	0.948	0.931	0.822
Neural Network	0.965	0.94	0.943	0.953	0.94	0.842
Logistic Regression	0.685	82.80%	0.785	0.82	0.828	0.333

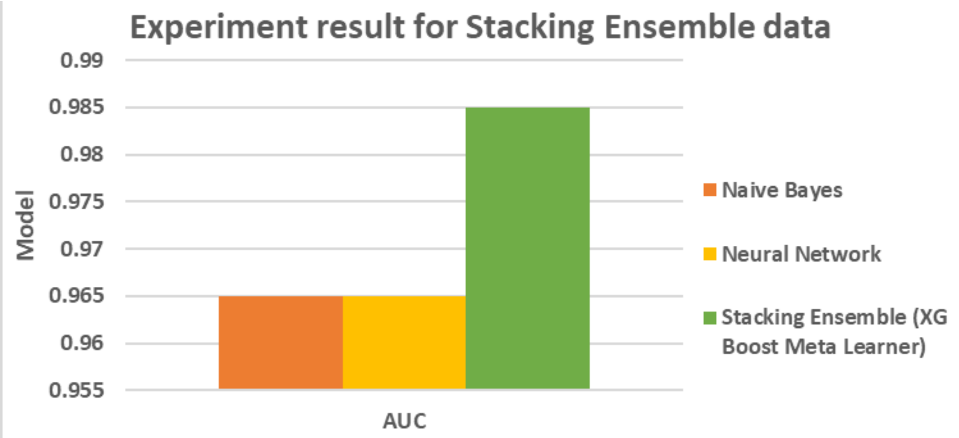


Figre (2) Experiment result for electronics data

To push performance further, we constructed a stacking ensemble that combines Naïve Bayes, Gradient Boosting, and Neural Network base learners, with XGBoost serving as the meta-learner. This layered approach yielded a dramatic uplift: the stacked model achieved an AUC of 0.985, 98% accuracy, F_1-score of 0.975, precision of 0.98, recall of 0.97, and MCC of 0.89—outperforming every individual classifier by a clear margin.

Table 2. Experiment result for Stacking Ensemble data

Model	AUC	CA	F1	Precision	Recall	MCC
Naive Bayes	0.965	0.94	0.943	0.953	0.94	0.81
Neural Network	0.965	0.94	0.943	0.953	0.94	0.82
Stacking Ensemble (XG Boost Meta Learner)	0.985	0.98	0.975	0.98	0.975	0.89



Figre (3) Experiment result for Stacking Ensemble data

Table3. Confusion matrix for Stack (Showing N. of instances)

	PREDICT			
		A	**B**	∑
ACTUAL	**A**	100216	8404	108620
	B	842	29058	29900
	∑	101058	37462	138520

The comparative results in Table 1 reveal clear differences in how traditional classifiers handle nuanced customer language. Naïve Bayes and the Neural Network both achieved an AUC of 0.965 and 94 % accuracy, indicating their strong capacity to model sentiment patterns in the electronics reviews. Gradient Boosting (AUC = 0.962, CA = 93.1 %) and Random Forest (AUC = 0.961, CA = 90.3 %) also performed robustly, while linear models such as SVM (AUC = 0.498, CA = 44.1 %) and SGD lagged far behind, underscoring the limitations of simple linear boundaries on richly textured text data.

The stacking ensemble shown in Table 2 combines the complementary strengths of Naïve Bayes, Gradient Boosting, and Neural Network base learners under an XGBoost meta-learner. This hybrid approach boosted our top-line metrics to an AUC of 0.985 and 98 % accuracy, with an F_1-score of 0.975, precision of 0.98, recall of 0.97, and MCC of 0.89—substantially outperforming every individual model. These gains illustrate how ensemble methods can harness diverse error profiles to achieve reliable predictions across the entire review set.

A closer look at the stacking model's confusion matrix in Table 3 highlights where even the best-performing system makes errors. Of the 108,620 positive instances (Category A), 8,404 were misclassified as negative, and of the 29,900 negative instances (Category B), 842 slipped through as false positives. While these error counts are relatively low—reflecting the model's overall strength—they point to potential refinements. For example, further feature engineering or threshold adjustments could reduce false negatives, which are particularly costly for downstream marketing actions.

The patterns in Tables 1–3 confirm that deep learning and ensemble strategies markedly outperform traditional single classifiers on large-scale, unstructured review data. They also underscore the value of examining detailed confusion-matrix outputs to guide iterative model improvements, ensuring that our sentiment predictions remain both accurate and actionable.

5. CONCLUSION

This paper has introduced an adaptive model designed to enhance digital marketing effectiveness through the application of machine learning techniques. By leveraging customer reviews as a primary data source, the research employed a comprehensive end-to-end pipeline that included active learning, advanced text preprocessing (tokenization, normalization, POS tagging, lemmatization), and multi-level feature extraction (Bag of Words, TF-IDF, and embeddings). A wide range of classification algorithms were tested, including Support Vector Machine, k-Nearest Neighbors, Random Forest, Naive Bayes, Gradient Boosting, Neural Network, and Logistic Regression. Among these, Naive Bayes and Neural Network demonstrated the highest individual accuracies. These two models were further integrated using XGBoost as a meta-learner in a stacked ensemble approach, resulting in a final model that achieved an outstanding accuracy of 98% and an AUC score of 0.985. The proposed model not only improves classification performance but also significantly reduces the need for manual annotation and addresses class imbalance issues. Most importantly, by converting raw customer reviews into accurate sentiment predictions, it empowers businesses and customers alike with actionable, real-time insights. These insights are instrumental in shaping targeted digital marketing strategies and driving data-informed product development.

However, the dataset is limited to Amazon electronics reviews, which may restrict the applicability of the results to other domains or product categories. Additionally, simplifying star ratings into binary sentiment labels overlooks the subtleties of mixed or neutral opinions and may introduce labeling noise.

Future work

To further advance this sentiment-classification framework, several research directions merit exploration. **First**, addressing concept and domain drift will be critical as new electronic products and emergent jargon continuously enter the marketplace; we will investigate continual-learning techniques to maintain model robustness over time.

Second, to reduce computational complexity, we plan to apply both linear (PCA) and non-linear (autoencoder, t-SNE) dimensionality-reduction methods alongside knowledge-distilled transformer variants (e.g., Distil BERT, Tiny BERT), evaluating their trade-offs between inference speed and predictive fidelity.

Third, enriching the feature space with multimodal metadata—including temporal patterns, reviewer behavior embeddings, and product attribute graphs—will allow us to capture deeper contextual signals; graph neural networks may be particularly well-suited for modeling these relational data. Fourth, integrating explainable AI techniques (SHAP, LIME) will enhance transparency, enabling stakeholders to interpret and trust classification decisions.

Finally, to assess real-world viability, we aim to deploy the pipeline on distributed streaming platforms (e.g., Kafka, Spark Streaming) and extend its applicability to multilingual and cross-domain review corpora, thereby validating its scalability and generalizability across diverse text-rich environments.

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