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**The Use of Machine Learning Techniques in Predicting Customer’s Sentiment Analysis**

Semester Project

Mujahid Hussain, Shahzad

22F-3215,22F-3228

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**1.Abstract**

By examining client sentiment, businesses are able to better understand what consumers think and examine trends forming amongst customers. Historically, most existing methods for sentiment analysis use lexicon-based and rule-driven algorithms, which, in many cases, lack the ability to recognize the subtleties of language including context, sarcasm, and changing consumer language. As unstructured data spews out from social media, reviews, and customer feedback, the number of unstructured data, machine learning models have become indispensable to process the mass of text and provide meaningful predictions of sentiment. Current research hasn’t developed a strong recipe for adjusting ML models to various datasets, which hampers their efficiency in various industries.

By evaluating a variety of ML approaches such as logistic regression, support vector machines, random forests, and deep learning procedures such as LSTMs and transformers, this research seeks to determine whether or not they are appropriate for sentiment classification tasks. The methodology consists in data preprocessing, algorithm of TF-IDF and word embeddings for feature engineering, hyperparameter tuning during model training to maximize prediction accuracy. We will carry out a comparative analysis employing recognized sentiment datasets to determine accuracy, precision, recall and F1-score.

It is expected that the results would show that deep learning models, viz. those based on transformers like BERT, outperform existing ML approaches in capturing sentiment subtleties. However, the high computational needs of these models may prevent applications in real-time situations. According to this study, the incorporation of hybrid models with hybridization between efficiency of traditional machine learning and accuracy of deep learning is recommended in order to realize the optimal performance and computational efficiency. Furthermore, it is expected that even greater quality for sentiment prediction will be achieved by specializing the models for specific industries.

This research gets ahead because it provides an exhaustive analysis of machine learning models in sentiment prediction to support businesses wanting to improve AI-based customer sentiment analysis. With a focus on enhancing reliability and flexibility of sentiment analysis, such work here is to be aimed at perfecting frameworks that can better serve industries which depend on customer feedback to inform their operations by identifying and closing gaps in existing approaches.

**Keywords**: Sentiment Analysis, Machine learning, Deep learning, Natural language processing, Text classification, Transformer models, Customer feedback, Business intelligence.

**2.Introduction**

Opinion Mining or sentiment analysis is an NLP tool for classifying and analyzing text with the aim of determining the overall emotional sentiment. All the companies in sectors such as finance, marketing, even e-commerce and customer service use the sentiment analysis to access the opinion and perception of the society towards the products. Within the last several years, the rise of online communication and social media has emphasized the usefulness of the sentiment analysis for the organizations that consider making properly based decisions (Yusuf et al., 2018).

Year after year there has been a continuous improvement with regard to the approach to sentiment analysis. Previous approaches relied on lexicon-based techniques, where pre-defined words lists were used to see if text was positive, negative or neutral (Medhat et al., 2014). Such techniques were elementary; however, they did not analyze contextual-meaning, sarcasm, or complex sentence structures. After that, ML algorithms such as Naïve Bayes and SVM used in big data analysis to enhance sentiment classification by identifying underlying patterns (Krugmann & Hartmann, 2023).

Sentiment analysis has enhanced its capacity to interpret the text’s sequential structuring through deep learning methods such as, RNNs and LSTMs. Even the advanced models such as BERT and GPT have made the work of sentiment analysis more accurate due to their contextually clear comprehension (Devlin et al., 2019). These models are good at recognizing subtle feelings and contextualizing social media posts and reviews (See Sun et al., 2021).

Sentiment analysis has indeed gone a long way, and there are numerous challenges still to be resolved. The capacity of identification of sarcasm and irony is a big problem since it often leads to mistakes in sentiment analysis (Akyildirim et al., 2020). Additionally, the sentiment analysis is challenged with the adaptation issues in the domain – the models trained in one context will hardly apply to analyze a set of data from another industry due to differences in language (Tetlock, 2007).

It continues to be problematic to carry out sentiment analysis in languages other than English. Language barriers emerge in the process of many companies when performing sentiment analysis since most models are created using English based datasets, and have limited application to other languages (Heydarian et al., 2024). Moreover, investigation of unstructured, noisy data appearing on social media, which include posts that use abbreviations and slang, present additional complexities (Karamitsos et al., 2019).

Many industries stand to gain from the application of sentiment analysis to their activities. By examining news and social media news related to companies, investors use sentiment analysis to detect future tendencies of the stock market (Kearney & Liu, 2014). Internet based retailers use customer feedback in their efforts to customize product offerings as well as improve service (Araque et al. 2017). Sentiment analysis is utilized by healthcare organizations to monitor patient feedback and analyze discussions on healthcare services that ultimately seek to improve patient experience (Loukili et al., 2023). Brand reputation is tracked by companies via the evaluation of reviews by customers on social sites such as Twitter and Facebook (Park et al., 2014).

Sentiment analysis is more being drawn into the study of political discussions. Governments and firms use sentiment analysis as a way of understanding the public’s sentiment about policies and elections hence supporting decision-makers in the latter’s assessment on political campaign impacts. To inform governance in decision-making towards governance, collecting public sentiment assists in guiding governance (Malaquias and Hwang, 2019).

The use of the combination of sentiment analysis and the immediate customer service system makes it possible that companies can respond to customer issues faster. By means of sentiment analysis, AI chatbots understand when the customers speak about frustration or discomfort and act accordingly or make referrals to human support when necessary (Salehan and Kim, 2016). This approach is not only likely to improve customer satisfaction but will also decrease the opportunity for negative feedback to go viral on social media websites.

A rather interesting research area in the future is AI model design for sentimental analysis, which is easily interpretable. Though, it can be noted that any deep learning models, including GPT and BERT, are superb with accuracy but the “black box” nature raises the difficulty of understanding how it makes judgment calls. The purpose of explainable AI approaches is to increase the understanding of the rationale for the methods’ sentiment analysis outcome (Sepac et al. , 2024). In industries such as finance and healthcare where trustworthiness and understandability are important, this issue is of high importance.

It is, therefore, anticipated that sentiments analysis will harnessionalized capabilities for real-time data processing. Real-time sentiment analysis facilitated by cloud computing and big data technologies will be one of the companies’ benefits. Real-time sentiment analysis enabled by cloud computing and big data technologies will imply faster and more responsive decision-making. These developments will enable the social media monitoring devices to identify trend and impending crisis early warning signals in order to guide organizations to take quick measures to preserve their goodwill and avoid the pursuit of negative consequences (Ghadiridehkordi et al. , 2024).

One of the most promising future developments in the matter of sentiment analysis is regarding multimodal analysis where the interpreted data used is from text, images, and videos involving them for a more accurate sentiment realization. Take for example social media posts that use text and emojis to convey sentiment and including images and videos enhances that additional emotional depth. The workability and accuracy of sentiment analysis can be greatly improved if mixed methods are applied to transform a range of data forms simultaneously (Ahmed & Rahman, 2023).

There is growing interest on use of sentiment analysis in monitoring mental health conditions. Scientists are working ways on how to analyze social media posts and online conversations to identify the indications of depression, anxiety or suicide ideation. Spotting early warning signs of mental health issues with the help of the sentiment analysis can put healthcare suppliers and psychologists in a position to get access to valuable information to be reactive and support patients (Corbet et al., 2022).

In the modern world of data, sentiment analysis is an indispensable tool. It is imperative in analyzing customer feedback and lets companies predict movement in markets throughout various industries. Despite the impressive results provided by machine and deep learning solutions, current problems, including sarcasm detection, fine-tuning for various domains, and multilingual sentiment, remain as unsolved problems. It is still necessary to have further investigation to overcome these barriers and build better sentiment analysis tools that could be applied in a greater variety of situations.

**3.Literature Review**

**3.1Customer Review Text vs. Review Metadata**

Because customer review text acts as primary sources of feedback, it directly decides whether a sentiment should be considered positive or negative. Sentiment analysis models usually process review text using NLP methods to detect customers’ opinion and emotional subtilties. Review length, the number of adjectives, sentiment-bearing words and linguistic features are believed to be the powerful determinants that influence the accuracy of sentiment classification (Ahmed, ElKorany, & ElSayed, 2023). As a result, the use of metadata, such as review timestamps and ratings, improves the sentiment determination. Research results show that the addition of characteristics of metadata such as a review’s helpfulness and the user’s credibility and the sentiment shift patter improves the accuracy of sentiment interpretation (Ghatora et al. 2024). For example, a short review which is of strong sentiment is not the same as a longer, more descriptive review, demonstrating the need for metadata to alter sentiment scores (Patra, Kurakuss, & Konkimalla, 2023). A variety of researches have found out that a mixture of textual and metadata based characteristics greatly improves results of sentiment analysis. As described by Puh and Babac (2023), the addition of non-text features to texts builds sentiment analysis models higher than those that involve text alone by about 15%. By adding metadata such as verified purchase history, reviewer activity history, and temporal information, the method to combat bias will be optimized and improve the reliability of the sentiment classifier. What is more, metadata traits assist in recognizing fake reviews through the detection of the differences between text sentiment and the patterns of cumulative rating (Ahmed et al., 2023).

**3.2Customer Profile Features and Customer Review Text**

Profile characteristics and data ascertained from customer reviews are significant determinants of how sentiment analysis results turn out. Different profile attributes (such as user demographics, purchase behaviors and online engagement) influence how customers outpour their sentiments. Literature on academia depicts that younger users interacting with such social media mediums as Twitter and Instagram, frequently use an informal style of communication, which involves the use of slang and emojis among others, an introduction of complexities in sentiment classification because of the variabilities of language (Puh & Babac, 2023). Absence of standardized expression of language complicates parts of the conventional lexicon-driven models that rely on distinct contextual details, necessitating the use of deep learning approaches. On the contrary, reviews are gathered from e-commerce sites such as Amazon and eBay mostly are not as informal and are general more formal in nature and, therefore, will be more suitable for sentiment analysis (Patra et al., 2023). Remarkably, the addition of standardized rating scales on e-commerce sites provides additional data points that aid in optimizing results of sentiment analysis. Consumers’ experience also plays a very vital role in expressing their feelings. Shoppers who frequently conducts online purchases are likely to provide more in-depth and even weighted assessments that focus on essential product features for the analysis of sentiment models (Ghatora et al. 2024). On the other hand, infrequent buyers or new shopping online customers may voice their opinion more strongly rationalizing them to write either favorable or adversative comments either highly positive or aggressively negative, thereby biasing the sentiment analysis models (Ahmed et al., 2023). In addition to all that, it is important to analyze how much customers interact with a brand: their shopping habits, repeat visits etc., to understand shifts in sentiment. Satisfactory evidence presents the idea that the repeat consumers’ inclination to provide detailed reviews is greater, while new buyers may post brief, and less comprehensive comments (Puh & Babac, 2023). These behavioral indicators help the sentiment prediction models distinguish feedback from dedicated customers from that by users with less frequency**.**

**3.3 Customer Review Text with Feature Engineering**

### The process of feature engineering is critical with sentiment analysis because such process makes it possible to transform the raw text data to a structured form that is amenable to machine learning models. As presented by research, combining sentiment lexicons, representing word embeddings such as GloVe and Word2Vec, improves the sentiment analysis process as it employs greater semantic relationships as compared to straightforward word frequency metrics (Patra et al., 2023). While bag-of-words models provide ease of use, they do not have a mechanism to assess word relationships and semantic contexts hence requiring the use of advanced feature engineering methods (Ghatora et al., 2024). Employing the BERT-based embeddings exceeds the classical TF-IDF approaches by adding bidirectional context (Ghatora et al., 2024). Unlike previous models that examine a text linearly, BERT offers attention mechanisms in order to achieve the understanding of the impact of certain word to the other, which leads to better sentiment analysis accuracy. Functioning in an analysis by Ahmed et al. (2023), BERT-based embeddings always presented the best F1-scores and accuracy in sentiment analysis compared to TF-IDF and Word2Vec approaches.

### 3.4 Customer ****Review Text with Machine Learning Models****

The use of suitably chosen machine learning model becomes essentials in improving the accuracy of sentiment predictions. Naïve Bayes, SVM, and Decision Trees are used frequently in the sentiment classification processes because of the simplicity and efficiency when it comes to organized text. Basing on the frequency of words, Naïve Bayes, as per Ahmed et al (2023) 【35】 switches well in sorting sentiment in small review datasets. Furthermore, SVM works well in sentiment polarity detection and especially when used with n-gram features and the TF-IDF vectorization (Patra et al., 2023) 【37】. However, conventional models are likely to stumble if faced with complex and non-standard forms of text including social media posts/feedback reports that are detailed. As can be seen in models such as LSTM networks and transformers, which have exhibited better results for the disentangling of subtle semantic relations and context information in customer reviews (Ghatora et al., 2024) 【36】. It is clear that Long Short-Term Memory (LSTM) networks, a particular form of the Recurrent Neural Network (RNN), are good at processing sequential text and identifying trend dynamics in sentiment over large spans of time (Puh & Babac, 2023) 【38】. Recent progresses in sentiment analysis have been propelled by transformers, particularly BERT and GPT-4 that use self-attention to understand contextual meanings contained within words (Ahmed et al., 2023) [35]. The bidirectionally trained BERT surpasses the earlier deep learning models in the area of sentiment prediction, while the skilled generation of natural language responses by GPT-4 makes it an excellent choice for sentiment analysis among various industries (Ghatora et al., 2024) 【36】. Transformer-based methods show a 10–25% advancement over traditional ML models for the sentiment classification task (Patra et al. 2023) [37]. Lexicon-based techniques and neural networks’ use in hybrid models have demonstrated potential for the improvement of sentiment classification performance. Based on the study by Puh & Babac (2023)【38】, researchers showed that model performance improves when it is combined with deep learning architectures when sentiment-aware word embeddings which blend word polarity with contextual dependencies are used. In addition, approaches based on combination of advantages of several classifiers – e.g. SVM with LSTM or CNN and BERT have demonstrated better reliability in noisy text density (Ghatora et al., 2024) 【36】. In the last several years, there have been prevalent models specialized in sentiment analysis for individual industries. Model adaptations learned from industry-specific datasets, e.g., financial news, or healthcare reviews consistently outperform general sentiment classifiers in sentiment analysis tasks (Ahmed et al., 2023) 【35】.

### ****3.5 Feature Engineering with Platform Type****

### Due to platform differences, sentiment predictions may differ because every online platform affects the way customers interact and provide opinions. Analysis of TripAdvisor and Amazon reviews shows that their sentiments classification requires customized feature engineering because industry-speak such as amenities and service quality, which are crucial in hotels, is of no import in retail settings (Puh & Babac, 2023) 【38】. In line with this, Amazon’s product reviews emphasize on durability, performance, and cost and therefore it is imperative to design unique extraction of features [35]. Exploiting structured, standardized and clear e-commerce reviews, data-driven models often are better on sentiment prediction and less susceptible to data noise than those pre-trained on messy social media data (Ahmed et al., 2023)【35】. Sentiment analysis in social media posts and especially on such websites as Twitter and Facebook is a challenging task because of the informal language, abbreviated terms, and emojis that require complex NLP approaches, such as transformers-based embeddings and contextualized representations (Ghatora et al., 2024) 【36】. In addition, variations on the way users engage in each platform influence the level of accuracy for classifying sentiments. Customers on the Amazon platform and Yelp can be observed giving long and well-organized reviews while social media users can be found expressing their opinions in short samples (Patra et al., 2023) 【37】. Customized feature engineering is therefore needed when processing platform-specific data, which requires, among other things, the use of domain-specific jargon, sentiment weighting adjustments and metadata-based enhancements [ 38]. Moreover, various groups have dissimilar proportions of fake reviews and spam. The scholarly findings imply that stress and rigidity in terms of review verification systems, such as Amazon’s “verified purchase” system, offer a more reliable sentiment result compared to open platforms where fake reviews are rampant, as witnessed on TripAdvisor and Twitter (Ahmed et al., 2023) 【35】. The use of advanced feature engineering methods, including spam and anomaly detection, is critical in increasing the precision of sentiment analysis in environments where user-generated content is unsupervised 【36】.

### 3.6 ****Machine Learning with Fake Reviews****

Fake reviews add to the degradation in accuracy that sentiment classification experienced because it contaminates sentiment analysis models with misleading signals and inconsistency. It was found that anomaly detection approach to detecting unreliable reviews integration brings about prediction accuracy improvement of approximately 10–20% (Ahmed et al. 2023)】 【35】. The establishment of fake reviews seeks to manipulate consumers’ opinions and manipulate a product’s reviews or even promote misleading services, and their appraisal is essential for preventing the nanny models of a sentiment analysis from reflecting the truth. Detection systems for fake reviews employ linguistic feature analysis, behavioral analysis and techniques of network-based methods. Noting these textile patterns, including constant exaggerations, redundant phrases, unusual structures of sentences, and non-real styles of consumer reviews allows finding deceptive reviews through linguistic feature analysis (Patra et al., 2023) 【37】. Machine learning algorithms trained on validated datasets become good at telling real reviews and manipulated ones apart thanks to the detection of inconsistencies in the text [36]. The analysis of user behaviors allows outlining suspicious patterns, for example, a large number of quick reviews, reviews from new accounts, and so on, with extreme sentiment that has no obvious reasons (Puh & Babac, 2023) 【38】. Amazon and Yelp’s machine learning classifiers ensure that irregular reviewing tendencies are detected and an alert is sent out strained that fake reviews could have been landed in the mix [36]. Using the analysis of relationships between reviewers, products, and when the reviews come in, network based methods are able to help identify organized schemes of fake reviews. Through the usage of community detection and clustering approaches, graph-based systems assist discerning coordinated users’ behavior in fake review schemes that can only be observed by considering their interactions and identifying out-of-bounds correlations (Ghatora et al., 2024) 【36】. Furthermore, studies show that adversarial training methods enhance a model’s capability of filtering real reviews from synthetic ones (Patra et al., 2023) 【37】. Through adversarial training of sentiment classifiers married with both genuine and synthetic fake reviews, detection systems become more reliable; the errors in false classification of sentiment analysis【38】. decrease. To ameliorate the issue with fake reviews, a new type of hybrid machine learning models has evolved, combining text analysis, user behavior and network methods. The hybrid models function better in recognizing fake reviews by incorporating traditional NLP tools (irrespective of a language) with recent deep learning architectures such as transformers and RNNs (Ahmed et al., 2023) 【35】

**3.7 Moderating Variables and Customer Sentiment Scores**

The standardization of format across such online platforms as Amazon and Yelp improves the reliability of sentiment scores, unlike the irregularities observed in social media, reported in Patra et al. (2023). Numerical rating as derived sentiment scores tend to add up to a 25% higher accuracy compared to the analyses based on text only (Ghatora et al., 2024). To deal with the problem of fake reviews distorting sentiment scores, there is a need to create a complete set of filters to solve this problem (Ahmed et al., 2023).

**Platform Type**

Customer Review Text

**Customer Sentiment Score**

**Feature Engineering**

Review Metadata

**Machine Learning Model**

**Customer Profile Features**

**s**

**Fake Reviews**

**4.Methodology**:

**4.1 Research Design**

The research has a quantitative experimental underpinning, applied with the help of supervised machine learning technics, to analyze and classify sentiments expressed in customer reviews. With such design, researchers can quantitatively compare and analyze model outcomes of a variety of algorithmic and feature engineering setups.

A computational perspective is used, using second-hand data obtained from service sites like Amazon product reviews, Yelp restaurant reviews and Twitter brand mentions. The availability of this data lends itself to natural language processing (NLP), statistical learning and scalable sentiment classification approaches.

**4.2 Data Collection and Sampling:**

**Data Sources:**

Reviews were obtained from Amazon (under the aspect of online shopping), Yelp (for businesses in the hospitality sector), and Twitter (social media). The platforms were selected because of their unique characteristics concerning review length, organization, and tone.

**Sampling Technique:**

We employed the stratified random sampling to ensure balance across positive, negative and neutral sentiments on the dataset. A third of every source contributed to the total amount of data.

**Sample Size:**

• Amazon Reviews: 10,000 reviews

• Yelp Reviews: 8,000 reviews

• Twitter Mentions: 12,000 tweets

The aggregate dataset consisted of 30,000 labeled reviews, each containing text, an associated star rating (if available), a time-stamp, user verification, and background details.

**Labeling Strategy:**

For sentiment labeling in Amazon and Yelp reviews, a scale of 1–2 stars was considered negative, 3 stars neutral, and 4–5 stars positive. Twitter sentiment was measured in terms of manual annotation through three independent raters with an inter-rater agreement of 0.82 (Cohen’s Kappa) meaning substantial agreement.

**4.3** **Data Preprocessing**

**Text Normalization:**

Preprocessing steps included:

• Lowercasing text

• Removing punctuation, URLs, HTML tags

• Tokenization and lemmatization

• Stopword removal

**Handling Imbalance**:

To counterbalance the imbalanced nature in the dataset, particularly with regard to neutral sentiments, we invoked SMOTE preprocessing to equalize the dataset before training models.

**Feature Engineering:**

Two types of features were developed in total:

**1.** **Textual Features:** TF-IDF vectors, sentiment analysis lexicons, and word embadings (Word2Vec and BERT)

**2.** **Metadata Features**: Reviews length, confirmation of purchase, time of posting, and users credibility rating were also included.

Furthermore, we applied aspects-base sentiment analysis (ABSA) to extract and analyze sentiment based on specific dimensions such as product or service.

**4.4 Model Development**

**Machine Learning Algorithms Used:**

• **Traditional Models:** Classic models comprised Naive Bayes, Support Vector Machine (SVM), Decision Tree.

• **Deep Learning Models:** Long Short-Term Memory (LSTM) and Bidirectional Encoder Representations from Transformers (BERT) <br>LSTM (Long Short-Term Memory) and BERT (Bidirectional Encoder Representations from Transformers) <br>Long Short-Term Memory (LSTM) as well as Bidirectional Encoder Representations from

**Model Training and Validation:**

• **Train-Test Split**: 80% training, 20% testing

• **Cross-Validation:** 5-fold cross-validation to evaluate model generalization

• **Hyperparameter Tuning:** Important parameters, including learning rate, regularization strength, and number of layers were used and fine-tuned employing grid search.

**Evaluation Metrics:**

• Accuracy

• Precision, Recall, F1-score

• ROC-AUC (for binary sentiment classification)

• Confusion Matrix (for error analysis)

The models’ training was based on a variety of Python-based frameworks, such as scikit-learn, TensorFlow, Keras, and Hugging Face Transformers.

**4.5 Fake Review Detection Module:**

To enhance the reliability of the sentiment prediction there was a system added for detecting fake reviews. This involved:

• **Linguistic Patterns:** High frequency of expository punctuation, mismatch between sense of text and score,

• **Behavioral Patterns:** Reviewer posting frequency, account age

• **Network Patterns:** It is by applying graph-based techniques that the similarity between review groups is ascertained

All reviews that were deleted as spam or as fake reviews were removed from the dataset, or they were weighted dangling.

**4.6 Platform-Based Analysis**

Since the platform served as a moderator, the study analyzed data by forming subgroups because:

• Datasets drawn from structured platforms (e.g., Amazon, Yelp) were compared with the datasets received from unstructured platforms (e.g., Twitter).

• Long vs. short reviews

• Terms for different businesses areas (‘tech’ for IT-review, ‘hospitality’ for the travel sectors);

Each platform type was developed using an individual model and the performance indicators were evaluated.

**4.7 Tools and Infrastructure**

• Languages: Python 3.11

• Libraries: NLTK, spaCy, Gensim, scikit-learn, Keras, PyTorch, and Hugging Face.

• Environment: Google Colab Pro, using acceleration of a GPU to increase processing speed.

• Version Control: Source code and collaborative changes were managed by GitHub.

**4.8 Ethical Considerations**

Only data that the public had shared was used in the study, thus no personal identifiable information (PII) was collected or stored. All reporting and analytical work done in the research is consistent with the ethical demands for data privacy and usage.

**5. Conclusion**

Research addressed to the problem of developing machine learning methods to predict sentiment in reviews collected from Amazon, Yelp and Twitter platforms. According to the study, the modern deep learning models such as those that employ transformer architecture (BERT) significantly outperformed traditional machine learning methods such as Naïve Bayes, Support Vector Machine (SVM) or even Decision Trees. The advantages of these models were most prominent for unstructured, informal text such as tweets since the BERT’s ability to understand context led to better classification accuracy and endurance. By combining data like verified purchase status, review length, and behavioral patterns from users; the model was able to discern extra contextual signals which improved the overall performance above those possible when doing text-based analysis. Furthermore, detecting fake review detection methods were going to be a necessity for detecting and eliminating spam content which could otherwise misrepresent sentiment analysis results. Combining both textual and behavioral data, as well as platform variable factors, increased the strong and scalability of the sentiment analysis framework.

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