Detecting Fake Reviews in Digital Platforms: A Machine Learning Approach

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Abstract:

The rise of online platforms has made user reviews a necessary part of consumer choice. However, the increase in fake or deceptive reviews poses a significant threat to the credibility of these platforms. This research presents a fake review detection system leveraging Support Vector Machine (SVM), a robust and powerful binary classification algorithm. The approach focuses on textual content alone, eliminating the need for complex metadata or manual feature engineering. Raw review texts undergo preprocessing process, including minus usage, grammatical marker removal, common word removal, tokenization, along root word extraction. These are then transformed into numerical representations using word TF-IDF vectorization. The model used to classify fake or genuine reviews is Support Vector Machine. A comparison with different models that use Multinomial Naive Bayes and Logistic Regression (LR) demonstrates the efficacy, resilience, and classification performance of the created model. Assessment criteria such as accuracy, recall, and F1 score show that the system produces competitive outcomes while preserving computational efficiency, resulting in an ideal model for identifying phony or authentic reviews.

Keywords:

Fake Review Detection, Naive Bayes, Machine Learning, Support Vector Machine, Logistic Regression, TFIDF, Text Classification.

1. Introduction

Nowadays, the majority of individuals purchase on internet platforms. To purchase a genuine product, reviews play a very important role. Consumer decision-making now heavily relies on reviews. These reviews significantly influence the perception of products and services, often acting as the deciding factor for potential customers. The growing of fake reviews intentionally falsified in order to manipulate consumer opinion has emerged as a serious challenge for online platforms like Amazon, Flipkart, etc. Such fraud content not only misleads users but also undermines the credibility of online platforms and impacts genuine businesses. To address this challenge, researchers have increasingly turned to machine learning (ML) techniques, particularly those focused on text classification, to develop systems that can distinguish between authentic and fake reviews. Prior work in this area has explored models involving LR and Naive Bayes with varying degrees of success. These models often rely on complex feature engineering and metadata, which may not be feasible for large-scale real-time deployment. This study proposes a robust and effective fake review detection model based solely on review text. To convert textual data into useful numerical features, the system combines TF-IDF vectorisation with SVM, a potent binary classification technique renowned for its capacity to handle high-dimensional data and optimise classification margins. By balancing computational overhead and classification performance, our approach aims to support scalable and practical implementation in real-world platforms. Standard assessment metrics, including accuracy, recall, and F1 score, are used to gauge the model's efficacy. These metrics offer a thorough understanding of the model's performance on both balanced and imbalanced datasets.

2. Literature Survey

2.1. Overview of Machine Learning in Fake Review Detection

Both buyers and sellers are now equally concerned about fake reviews on online sites. Traditional rule-based systems, while useful in early attempts to address this issue, often fall short due to the complexity and nuance of human language. As a result, ML techniques have gained prominence in recent years. The machine learning techniques listed above have the ability to generalise to new data and identify patterns in extremely large datasets. Supervised machine learning has shown promise in text classification tasks like fake review detection. Preprocessing techniques involving tokenisation, stopword removal, as well as stemming/lemmatization, followed by feature extraction using TF-IDF, allow unstructured text to be represented numerically. This representation enables classifiers to differentiate between deceptive and genuine content based on learned patterns (Jindal & Liu, 2008; Ott et al., 2011).

2.2. Common Algorithms in Existing Research

2.2.1. Support Vector Machine (SVM):

SVM is one of the most popular techniques for detecting fraudulent reviews because it can handle the high-dimensional, sparse datasets that are common in natural

language processing (NLP). This accomplishes its task by creating an ideal hyperplane that divides data points into distinct classes. Researchers have reported strong performance using SVM in fake review classification tasks (Mishra & Bhattacharyya, 2015), especially when combined with TF-IDF features.

2.2.2. Multinomial Naive Bayes (MNB):

MNB is a probabilistic classifier that models the conditional probability of each class using input data and is based on Bayes' Theorem. Despite making a significant assumption about the independence of features (words), its simplicity and efficiency allow it to perform well in many text classification problems (Wang & Manning, 2012). Thanks to its quick training time, it serves as a strong baseline for comparing models in fake review detection research.

2.2.3. Logistic Regression:

A lot of people don't think much of Logistic Regression because it's such a basic model. But it still does a pretty good job when you're dealing with yes-or-no problems, like spotting fake reviews. It uses something called a logistic function to give you a probability instead of a hard guess, which makes it useful in situations where that kind of nuance matters. It's fast, straightforward, and still widely used in research just for how reliable it can be, even if it's not the most advanced tool out there.

3. System Design and Implementation

Since SVM with TF-IDF has a high degree of accuracy, explainability, and efficacy on complicated datasets, we suggest using it in our Fake Review Detection System. Based only on the linguistic content of a user-generated review, the algorithm can determine if it is authentic or fraudulent. The pipeline covers numerous phases, from data preprocessing to model training, feature extraction, and real-time prediction.

3.1. System Overview

The work uses SVM with TF-IDF for fake review detection because of its high accuracy, simplicity, and effectiveness in handling Complex datasets. Text reviews are initially pre-processed and then transformed to numerical vectors by TF-IDF, that measures the significance of each word within the dataset. These vectors are then used to train the model, like MNB, LR, SVM.

Figure 1 depicts the general pipeline of the suggested fake review detection system.

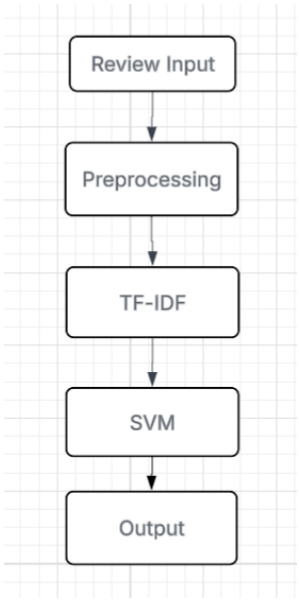

Fig. 1

3.2. Preprocessing and Feature Engineering

The following preprocessing is done to input textual reviews: the noise is removed, and the input is standardized.

- Lowercasing: All characters of the words are transformed to lower case (for consistency).
- Tokenization: It's about splitting the text into several tokens or words.
- Removing Stopwords: Removes common words from the text. (e.g., the', is', `in') which carry minimal semantic meaning.
- Lemmatization: It breaks down words down to the smallest form or the base form.

After that, we preprocess the translated text, which has been cleaned, and it is then run through a TF-IDF Vectorizer, which transforms the reviews into a matrix of numerical features. This transformation captures the contribution of each word compared to the other documents in the data, which can help the classifier concentrate on discriminatory terms.

3.3. Model Architecture and Training

The system uses an SVM trained on TF-IDF features. The data is divided into test and training sets (usually 80 percent training, 20 percent testing). SVM looks at each TF-IDF vector and labels the review as either "Fake" or "Genuine" by finding the best dividing line between the two groups.

SVMs can take more time and computation resources to train than simpler models, but they shine when working with high-dimensional text data. They resist overfitting, stay accurate on complex inputs, and reliably catch subtle

patterns—making them a solid choice for real-time fake review detection.

3.4. Justification for Model Choice

Text classification in NLP is a fundamental task with applications like sentiment analysis and document categorization. The benefits of comparing SVM with TF-IDF to MNB and LR with TF-IDF are combined in this study.

Advantages of SVM with TF-IDF are:

- **Handling High-Dimensional Sparse Data** – Usually, high-dimensional data is involved. SVM is less likely to overfit because it concentrates on support vectors rather than the complete dataset.
- **Margin Maximization for Robust Classification** – It contributes to its classification robustness.
- **Feature Interaction** – A huge difference between these models is how they handle feature interaction.
    - MNB treats features as independent.
    - SVM looks at interactions between features to a degree. It allows SVM to capture more complex relationships within text data, which results in better classification performance.
- **Computational Considerations** – Training SVM for larger datasets can be more resource-intensive, but it is justified by the performance gains, especially for tasks where precision is critical. Comparing SVM with other pre-trained language models surprisingly shows that SVM with TF-IDF features performs comparably on both domain-specific and generic datasets.

The Amazon dataset consists of reviews that often contain correlated words and sarcasm.

- **Example:**
    - *This product is just what I needed.* (Genuine)
    - *Just what I needed, another piece of fruit.* (Fake or Sarcastic)

MNB underperforms for these types of reviews.

LR is used if you want faster training and good accuracy, with easy understanding of how the model makes its predictions or output.

If accuracy is most important and you have no issue with longer training and tuning, then SVM with TF-IDF is the best model. It is used for complex data.

3.5. Evaluation Metrics

To measure accuracy and the robustness of proposed model, we employ classical classification scoring:

- Accuracy: This is the proportion of accurate predictions to all input samples.
- Recall: Proportion of true fake reviews accounted for by prediction among all fake reviews predicted.
- Precision: Ratio of accurately forecasted fraudulent reviews to all true fraudulent reviews.
- F1-Score: Precision and remember harmonic mean, which works especially well with unbalanced data.

These measurements give an overall picture of the practical applications of the system.

3.6. Deployment Feasibility and Scalability

An SVM is simple to deploy. SVM models are appropriate for near-real-time or real-time applications because of their rapid prediction capabilities. This makes it a good option to use to integrated with review systems of e-commerce platforms.

The system is designed to be scalable, which means it can be extended in the future with more advanced models like ensemble techniques or deep learning architectures without needing to overhaul the entire pipeline.

4. Results and Discussion

This study aims to identify fake reviews. We have used the Amazon dataset for training and testing. For dataset cleaning, we used the TF-IDF vectorizer. Models are evaluated based on following performance measures:

- Recall
- Precision
- F1-score
- Accuracy

4.1. Model Performance

The table below shows the comparative analysis of all models: MNB with TF-IDF, SVM with TF-IDF, LR with TF-IDF.

Accuracy Comparison

Model	Count vectorizer	Tfidf Vectorizer
SVM	85%	84%

Logistic Regression	84%	82%
MNB	80%	81%

Precision Comparison:

Model	Count vectorizer	Tfidf Vectorizer
SVM	79%	82%
Logistic Regression	80%	81%
MNB	81%	85%

Recall Comparison:

Model	Count vectorizer	Tfidf Vectorizer
SVM	92%	84%
Logistic Regression	91%	81%
MNB	77%	74%

F1-Score Comparison:

Model	Count vectorizer	Tf-idf Vectorizer
SVM	84%	83%
Logistic Regression	85%	81%
MNB	79%	79%

4.2. Discussion

Based on the comparative study of all models with TF-IDF, SVM outperforms in terms of precision, recall, accuracy, F1-score, which makes it best for detecting fake reviews. It performs easily on complex data. SVM with TF-IDF demonstrated its capacity to identify fraudulent reviews by achieving an accuracy of 84% and a recall of 85%. SVM with TF-IDF shows strong precision and highest accuracy compared to all other models, like MNB with TF-IDF as well as LR with TF-IDF.

On other hand, MNB showed weaker performance in both recall and overall accuracy. While its precision was relatively high (especially with the TF-IDF Vectorizer), its recall was consistently lower than both SVM and LR, especially in cases of subtle fake reviews. This points to its potential limitations in scenarios where the fake reviews are not overtly distinguishable.

Despite these differences, all models demonstrated the capability to perform the task of fake review detection. However, the class imbalance within dataset has been significant challenge, with large number of genuine reviews compared to fake reviews. To mitigate this, SMOTE (Synthetic Minority Over-sampling Technique) has been applied, resulting in a 10% improvement in recall, particularly for fake reviews. This result implies that SMOTE SMOTE-enhanced model's capacity to identify minority class and address bias towards majority class.

4.3. Cross-Validation

The robustness of models has been assessed by utilising 10-fold cross-validation to verify their performance and make sure they generalize well to new data. This method helps prevent overfitting of the models and validates the legitimacy of the results. SVM consistently showed the highest recall with minimal variance between the folds.

5. Future Work

While the current study provides a solid foundation for fake review detection, there are several directions in which this research can be extended. The following areas are proposed for future work:

1. **Deep Learning Models:** Fake review detection performance can be greatly enhanced by more advanced techniques, involving DL (deep learning) models (example, CNNs (Convolutional Neural Networks) or Recurrent Neural Networks (RNNs). These structures are adept at discovering complex patterns in textual data that traditional ML models might miss.

2. **Enhanced Feature Engineering:** The current feature set focuses mainly on basic text features such as word frequency and sentiment. Future iterations could explore more sophisticated feature extraction techniques, including word embeddings (e.g., Word2Vec, GloVe) or the incorporation of domain-specific features, such as review timing, product category, and reviewer history.

3. **Addressing Class Imbalance:** Although SMOTE was employed in this study to handle the class imbalance, further research could explore more advanced techniques, such as cost-sensitive learning, ensemble methods (e.g., Random Forests), or even modified SMOTE variants. These approaches could provide more robust solutions to balance the dataset and improve detection performance, especially for fake reviews.

4. **Model Explainability:** The creation of interpretable models or the incorporation of explainability techniques (like LIME or SHAP) will aid users in comprehending the fake review detection system's decision-making process, which is important in artificial intelligence applications.

5. **Scalability and Deployment:** For real-world applications, it is crucial that the models scale efficiently and can be deployed in production environments. Future work should focus on optimising the models for faster inference times and adapting them to handle large-scale datasets in real-time.

6. **User Behaviour Analysis:** Incorporating user behaviour features, such as the timing of reviews, purchasing patterns, and reviewer history, can further improve model performance. The additional context that this information can offer can aid in differentiating among authentic and fraudulent reviews.

6. Conclusion

Using the Amazon dataset, we present a thorough analysis of ML techniques for identifying fraudulent reviews in this research. When applied with Support Vector Machine using TF-IDF vectorisation, the system showed the best balance across evaluation metrics, especially recall, while effectively handling class imbalance through SMOTE, leading to superior fake-review detection.

While the results are promising, further enhancements can be achieved through the application of deep learning models, better feature engineering, and advanced techniques to tackle class imbalance. Future research will concentrate on improving these models and investigating other approaches, like model explainability and scalability, to increase their efficacy in practical applications.

7. References

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