

Fake Product Review Detection Using Machine Learning

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Abstract.

Online product reviews play a crucial role in the purchasing pattern of customers. Fake reviews may mislead consumers. A large number of fake reviews will even cause huge property losses and public opinion crises. Therefore, it is necessary to detect and filter fake reviews. To solve this problem, a novel technique to detect fake reviews has been proposed. Credibility of online reviews is crucial for business and can directly affect companies reputation and profitability. The proposed technique deals with the usage of URL's and IP addresses for identifying fake reviews. The designed algorithm is expected to achieve high accuracy levels.

1 INTRODUCTION

With a rapid growth in technology, a variety of jobs which took ages to complete were finished in fraction of that period. However, in hindsight, a large amount of misuse of technology leading to cybercrimes have reason in recent times. Phishing attacks deceive users by not only stealing their information but also pass fraudulent messages there by providing misleading information. One of the areas deal with sending fake review messages.

It is a known fact that a large number of human beings read review information about a product before actual purchases. Fake reviews tend to disrupt the buying habits of users eventually leading to their dissatisfaction. An additional problem that can arise due to fake reviews is damage to the reputation of the company.

A large amount of money has been spent to detect cybercrimes which keep increasing with each passing day. To overcome the same, urgent measures must be taken to find a solution for the same. Since reviews published by reviewers are uncertain and the fact that there is an unknown aspect to the credibility of reviews, an evaluation index system needs to be designed that is able to judge the authenticity of reviews.

As intelligent scammers are able to cleverly make fake reviews appear real, complex machine learning techniques must be used for accurate detection. This work accepts URL's and IP addresses and uses a combination of XG boost and Random Forest algorithms for finding its genuineness.

URL based methods have the distinct advantages of detecting a fake message without clicking on the URL. By accurately screening the fake reviews and making them unavailable for users view,

the level of user satisfaction can be enhanced significantly.

2 LITERATURE SURVEY

Until the early part of 20th century, the advancement in technology has been growing at a snail's phase. The number of different types of products were limited. Most of the products exhibit a high level of quality. However, the latter half of 20th century saw a rapid growth of technology. Besides, a large number of tools were also designed to cater to many applications. The growth of technology also allowed heavy misuse of the same. Owing to a section of people, a number of fake products started coming into existence.

The late 1990's dealt with a large number of tools pertaining to networking. During the year 1992, Harris and his team designed an application [1] that provided the internet with autonomous intelligence that was distributed throughout the network. During the year 1996, Bernhard West Fechtel performed an analysis by constructing variety of graphs for combining set of products and processes [2]. They were able to demonstrate how concurrent engineering is supported through the process of exchanging pre-releases of intermediate results. During the year 1998, Fan Yushun and Wu Cheng designed a tool [3] for increasing the speed of integration of products. Wu Cheng improvised on the work done by his predecessors by designing a tool for increasing the speed of integration of products. The beginning of the 21st Century saw a rapid growth in science. New algorithms were formulated at breadth neck speed. During the year 2002, Wan Xiang and his team incorporated a clustering algorithm [4] for connection of manet and internet. They used a number of parameters like pohler, movement probability and hop length. The simulation results showed that this clustering technique is found to be more robust and has less overheads. One more feature which was primarily needed by customers is on time delivery of the product. Charlene Spodee Budd, and Marjorie adopted two different approaches [5] namely Critical path method and Critical chain method in the year 2005. They found that there was significant amount of saving in time while using chain method with critical path method.

During the year 2008, Qiu Lingyun and Li Dong considered an online shopping model [6] focusing exclusively on parameters like perceived usefulness, ease of use, trust, social presence and perceived enjoyment. They also found the relationship between these parameters.

After 2010, with rapid usage of social media, the number of reviews ran into millions. During this period, the number of fake reviews also increased multi-field. The need for a new technique arose for identifying genuine reviews. During the year 2017, Lu Zhang and his team designed a partially supervised learning model [7] for detecting spammer groups. They used a combination of naive Bayes algorithm and expectation maximization algorithm for constructing a classified as spammer Group detector. During the same year, Neng Li and his team considered the specific domain of farming [8]. They considered community based features and user-based features like Support vector machine, K-nearest neighborhood and Random forest for distinguishing between a genuine farmer and a fake farmer. During the year 2018, Suyuan Luo and Shaohua Wan improvised [9] on the work carried out by fellow researchers by formulating a conceptual framework for extracting the characteristics of fraudulent transactions.

During the year 2019, Jindi Fu and his team worked on the prospects of collaborative shopping [10]. They surveyed a group of 233 customers and analysed their buying behaviour. They used a number of similarity coefficients for finding the group of buyers with similar traits. This in turn could provide

the vendors with ideas on collaborative shopping.

With passage of time, a number of companies formulated strategies for increasing spam reviews in order to boost the company's name, recognition and profit. Online reviews had become the main source for determining public opinions. To overcome this problem, during the beginning of 2020, Hussain and his team detected spam reviews [11] using two methods namely behavioral and linguistic. They found that the behavioral model generated an accuracy of 93.1% linguistic model generated an accuracy of 88.5% the end of the year, Meiling Liu and her team considered additional factors for detecting fake reviews. They found that the existing techniques do not consider the implicit patterns among users, reviews and products.

During 2021, Jianrong Yao and his team combined resampling with Grid search technique [12] for identifying the appropriate features off irrelevant and unnecessary parameters and optimize the model. A similar analysis was carried out in the year 2022 by Thi-KimHien and his team [13]. The team also considered linguistic and behavioral aspects. They proposed a hierarchical logistic regression technique and found that the designed model performed better than existing model. During the year 2023, Rosario and her team exploited the usage of two language models [14] namely Bert and Electra in a new Italian data set that pertains to cultural heritage of Italy. They were able to achieve an accuracy of 95% detecting fake reviews. During June 2023, Mehedi and his team designed a number of methods [15] like expert based manual fact checking, crowd source fact checking and deep learning techniques for detecting fake news. During the end of the year, Mohammad Ennaouri and Ahmed zelleou performed a [16] comprehensive analysis of various machine learning techniques for identifying fake reviews.

One more survey of deep Learning techniques for fake news detection was performed [17] in the year 2024 by Enaiafe Festus Ayetiran and Ozlem Ozgobe. It was observed that however good a technique is, it can identify false review only to a certain extent. To find a solution to this problem, Samia and her team adopted a fusion approach [18] where they combined the characteristics of a number of techniques like CNN and aspect-based analysis. Appropriate weightages were given to each aspect of the network and it was found that the proposed model outperformed existing models on both review authenticity and aspect analysis. This innovative approach gave an accuracy of 97.75% In order to fine tune and validate the research, this work focuses on using ML Algorithms like XG Boost and Random Forest for identifying fake websites.

3 METHODOLOGY

Our proposed approach for fake review detection involves the following steps:

- Data Collection: Reviews are sourced from multiple e-commerce platforms.
- Feature Extraction: URL structures and IP metadata are analyzed.
- Machine Learning Models: We use XGBoost and Random Forest classifiers.
- Evaluation Metrics: Accuracy, Precision, Recall, and F1-score.

4 GENUINNESS OF PRODUCT REVIEWS

Fake product reviews are a significant challenge in ecommerce, affecting consumer trust and product credibility. Machine learning has emerged as a robust solution to identify and mitigate such reviews by analyzing textual patterns, metadata, and user behavior. The process begins with data collection, where reviews are sourced from platforms like Amazon, Yelp or TripAdvisor. These

datasets may include labeled examples of genuine and fake reviews, often identified through verified purchases, platform moderation or expert assessments. Public datasets such as Yelp's Fake Review Dataset are also widely used for research and development. The collected data typically includes the review text, ratings, timestamps, reviewer profiles and other metadata that help in detecting anomalies indicative of fake reviews.

Data preprocessing is a critical step in the pipeline, aimed at cleaning and organizing the raw data for analysis. Text preprocessing involves removing unnecessary elements like HTML tags, special characters and stop words to ensure that text is standardized. Tokenization breaks the text into smaller units, such as words or phrases, while stemming and lemmatization reduce words to their root forms, making analysis more efficient. Behavioral features are also incorporated, focusing on patterns like sudden surges in reviews, reviewer activity and metadata like account age or verified purchases. Sentiment analysis can further provide insights by identifying unnatural patterns, such as overly positive or negative sentiments that deviate from normal user behavior.

Feature engineering combines these textual and behavioral elements to create a robust input for machine learning models. Textual attributes such as word frequency, sentiment polarity and the use of specific linguistic styles like excessive adjectives or repetitive phrases are common indicators of fake reviews. Metadata-based features include temporal patterns, such as bursts of reviews within a short period, and reviewer traits, such as submitting reviews for unrelated products or writing near-duplicate content. These features are fed into machine learning models to classify reviews as fake or genuine.

Machine learning models for fake review detection range from traditional algorithms to advanced deep learning approaches. Traditional models such as logistic regression, support vector machines (SVM) and random forests are widely used for their simplicity and efficiency. Ensemble methods like gradient boosting (e.g., XGBoost and LightGBM) often provide superior performance by combining multiple weak classifiers into a strong one. For more complex textual data, deep learning models like recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and transformers are employed. These models excel in capturing contextual and sequential patterns in text, making them highly effective for natural language processing (NLP) tasks. In cases where labeled data is limited, unsupervised methods such as clustering and anomaly detection can identify suspicious reviews based on deviations from normal patterns.

Model evaluation is essential to ensure the effectiveness of the system. Common metrics include accuracy, precision, recall, and F1 score, which measure the model's ability to correctly classify fake and genuine reviews. The area under the receiver operating characteristic curve (ROC-AUC) is also used, particularly in scenarios with imbalanced datasets, where the number of genuine reviews far outweighs fake ones. Techniques like oversampling, under sampling or using synthetic data generation methods like SMOTE are employed to address this imbalance.

Despite effectiveness, machine learning-based fake review detection faces several challenges. Fraudulent reviewers continually adapt their tactics, requiring regular updates to models and features. Imbalanced datasets can lead to biased models, necessitating careful handling during training and evaluation. Ethical and privacy concerns also arise, as analyzing reviewer data must be done responsibly to avoid violating user rights.

Additionally, over-reliance on automated systems can result in false positives, where genuine reviews are incorrectly flagged as fake, potentially harming the reputation of honest users.

5 TOOLS

For efficient demonstration, an aesthetic view is needed for clear presentation and demonstration. Although a number of tools are in place, the appropriate choice of tool plays a major role in projecting the appropriate details. Power BI plays a crucial role in detecting fake product reviews through its integration with machine learning techniques, such as the XGBoost algorithm, for identifying fraudulent reviews effectively. XGBoost, a highly efficient gradient boosting model, is used for classifying reviews as genuine or fake by analyzing features such as sentiment, reviewer activity and review text. Power BI enhances the analysis process by providing an interactive platform for visualizing the results of these machine learning models.

It connects to various data sources, such as review databases and customer profiles, enabling the seamless integration of XGBoost predictions into interactive dashboards and reports. With Power BI's advanced analytics capabilities, businesses can visualize key metrics such as the accuracy of the XGBoost model feature importance, and trends in fraudulent reviews across different product categories. Visualizations like bar charts, scatter plots and heatmaps allow stakeholders to explore review patterns and gain insights into suspicious behaviors enabling proactive actions to maintain product authenticity. By tracking Key Performance Indicators (KPIs), Power BI facilitates better decision-making, helping businesses improve customer trust and ensuring a more transparent review system. KPI's include attributes like the percentage of fake reviews detected and improvement in product ratings.

The graph shown in Fig 1. clearly shows that the count of reviews are higher in Earphones compared to other gadgets.

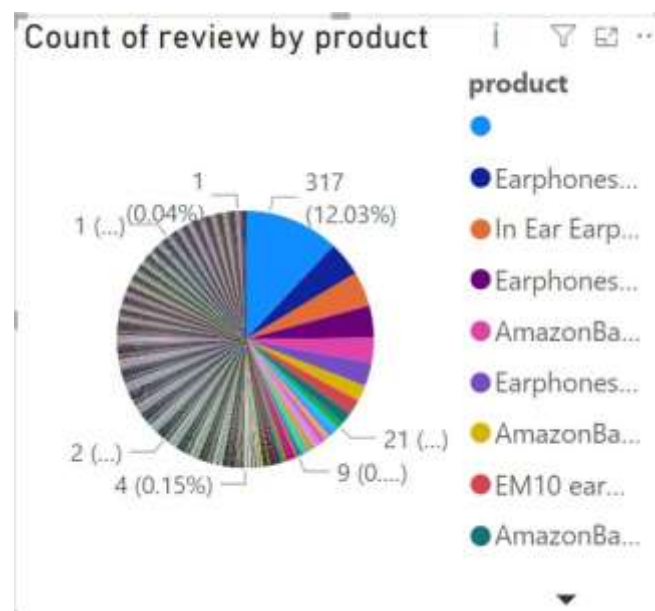


Fig 1. Count of Reviews by Products

The graph shown in Fig 2. clearly shows that the sum count of reviews are higher during the years 2015 and 2016.

The bigger challenge lies in the fact that a number of reviews could be fake. The demonstrated technique is able to identify the set of genuine and fake reviews. A set of reviews for 2500 electronic items, 1800 clothes, 1000 cosmetics and 2000 footwear items were analyzed using this algorithm. It was found that approximately one in three reviews were found to be falsely generated. On the whole, 30fake. This information has been clearly demonstrated in Fig.4.

```
Column Names in the Dataset:
['url', 'review_bold', 'ratings', 'review', 'verified', 'date', 'by', 'profile_id', 'most_rev', 'by_link', 'helpful', 'product', 'product_link', 'review_sentiment']
Please enter the product URL to check: https://www.amazon.co.uk/gp/review/R582DAW13X2P/
The product is real.
```

Fig.5 Display that the given URL is Real

```
Column Names in the Dataset:
['url', 'review_bold', 'ratings', 'review', 'verified', 'date', 'by', 'profile_id', 'most_rev', 'by_link', 'helpful', 'product', 'product_link', 'review_sentiment']
Please enter the product URL to check: https://www.amazon.co.uk/gp/review/R280T0WVZ30EN/
The product is fake.
```

Fig.6 Display that the given URL is Fake

This system is able to identify the genuiness of the product given its URL. Snapshots showing Real and Fake URL's have been shown in Fig.5 and Fig.6.

Table 1. Model Performance Metrics

Model	Accuracy	Precision	Recall
XGBoost	92%	91%	90%
Random Forest	89%	88%	87%
SVM	85%	83%	82%

7 CONCLUSION

An efficient machine learning algorithm has been found to be highly efficient in detecting the genuiness of product reviews. By providing the appropriate URL's and IP addresses, XGBoost machine learning algorithms were able to identify the genuiness of a product with an accuracy of 92%.

The novelty in this approach lies in the fact that even if one of the inputs is not provided, the algorithm is able to maintain this accuracy level. With the database containing a large number of IP address available to human beings for a variety of purposes, chances are that errors can creep up. Errors include digits erroneously getting replaced by other digits or a digit may be inadvertently missed out owing to the mistake of the operator or other reasons. The innovative features inbuilt in the designed algorithm is its ability to foresee such issues and also make an automatic correction on the same.

Machine learning provides a powerful approach to combating fake product reviews by leveraging a combination of NLP, behavioral analysis, and advanced modeling techniques. By incorporating both textual and metadata features, these systems can effectively identify fraudulent activity and maintain the integrity of online review platforms. Continuous advancements in machine learning, coupled with ethical considerations and robust evaluation will be crucial for addressing the evolving nature of fake reviews and preserving trust in e-commerce ecosystems.

Perfection is a keyword that is found only in the dictionary. Although 100 techniques could be devised for increasing the accuracy levels. This work can be combined with other machine learning

algorithm or achieving accuracy of more than 95 steps could be taken for completely eliminating the fake reviews before they come into customer's views. This in turn could go a long way in increasing the levels of customer satisfaction while purchasing the product.

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