



Poster: Leveraging Data Analysis and Machine Learning to Authenticate Yelp Reviews through User Metadata Patterns

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ABSTRACT

Due to the technological revolution, online reviews have become extremely valuable to consumer decision making, with approximately 93% of all consumers relying on reviews for purchasing decisions. However, the rise of fake online reviews has raised concerns about their trustworthiness, as it is estimated that 4% of all internet reviews are estimated to be fraudulent, impacting worldwide online purchases by \$152 billion. This prevalence not only misleads consumers but also challenges businesses striving to maintain their reputation. Yelp, a prominent platform hosting online reviews, plays a crucial role in shaping consumer perceptions and purchasing choices. However, the presence of fake reviews on Yelp has raised integrity concerns. This research explores the use of data analysis techniques and machine learning algorithms to determine the authenticity of Yelp reviews, contributing to the enhancement of the credibility of online review systems, enabling informed decisions, and promoting fair competition among businesses.

CCS CONCEPTS

• Computing methodologies → Semi-supervised learning settings; Machine learning; • Information systems → Evaluation of retrieval results.

KEYWORDS

Consumer Decision-Making, Fake Reviews, Data Analysis, Machine Learning, User Metadata, Yelp Reviews, Logistic Regression

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1 INTRODUCTION

In the digital age, online reviews have become an integral part of consumers' decision-making process, influencing their purchasing choices and shaping their perceptions of businesses. According to

recent statistics provided by reputable e-commerce sites, a staggering 93% of customers read reviews when purchasing a product online. However, with the rise of fake online reviews, the trustworthiness and reliability of these reviews have come into question. It has been estimated that approximately 4% of all internet reviews are fraudulent, contributing to a \$152 billion direct impact on worldwide online purchases. This prevalence of fake reviews not only misleads consumers but also poses significant challenges for businesses striving to maintain their reputation and attract genuine customers.

Among the prominent platforms hosting online reviews, Yelp stands as a leading player in the consumer review space. With its vast user base and extensive collection of reviews, Yelp plays a crucial role in shaping consumer perceptions and influencing their purchasing decisions. However, the presence of fake reviews on Yelp has raised concerns about the integrity of its review system and the reliability of the information provided to users.

The impact of combating fake Yelp reviews goes beyond consumer choices. It influences business competitiveness, market dynamics, and genuine establishments' well-being, necessitating effective strategies to counter such reviews.

This study aims to employ data analysis and machine learning to authenticate Yelp reviews. Through these techniques, the goal is to build models that can accurately detect fake reviews, ultimately enhancing the credibility of online reviews, enabling informed consumer choices, and fostering fair competition.

2 RESEARCH QUESTIONS

Can data analysis techniques and machine learning algorithms be used to accurately determine the authenticity of Yelp reviews based on patterns among user metadata?

- What features are important for fake review detection?
- Can we train models to detect fake reviews?

To achieve these research objectives, this study will involve the extraction and analysis of data and text from Yelp reviews, the annotation and interpretation of the collected data, and the application of data analysis techniques and machine learning algorithms to develop models for fake review detection. The findings of this research will be presented in the form of a research paper and accompanying presentation, contributing to the existing body of knowledge on disinformation detection and authenticity assessment in online reviews

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3 FAKE REVIEWS ON YELP AND YELP'S EFFORTS TO COMBAT THEM

3.1 What is Yelp?

Yelp, a popular online platform, provides a space for users to share their experiences and opinions about businesses through reviews. However, the prevalence of fake reviews on Yelp undermines the credibility of the platform and poses a challenge to both consumers and businesses. Yelp has implemented various measures to combat this issue and ensure the reliability of the reviews it showcases.

3.2 Yelp's Recommendation Software

Yelp employs automated recommendation software that evaluates reviews based on signals of quality, reliability, and user activity. The software's objective is to showcase the most helpful and reliable reviews, providing a level playing field for all businesses. It analyzes billions of data points from reviews, reviewers, and businesses to assess the usefulness and reliability of each review. By applying objective rules to every business and treating reviews of advertisers and non-advertisers equally, Yelp aims to filter out biased and unreliable reviews.

3.3 Why Yelp/Research Significance

The implementation of recommendation software is a step in the right direction, but the battle against fake reviews remains challenging. The limitations of automated systems and the constant evolution of deceptive tactics underscore the need for ongoing vigilance and adaptation.

Despite the ongoing challenges, researching the issue of fake reviews on Yelp remains crucial. The impact of fake reviews on consumer decision-making and the credibility of online platforms is a significant concern. By investigating the economic incentives, prevalence, and effectiveness of Yelp's efforts, our research question sheds light on the complexities of this issue.

4 METHODOLOGY

The research methodology involved collecting data from Yelp business pages using Python with the BeautifulSoup library to extract review details. The collected data was processed, and a GitHub repository with labeled Yelp reviews was utilized to create a dataset of real reviews. After standardizing and combining the datasets, pandas was used for analyses like review length and visualizations. The subsequent step was training a Logistic Regression model with TF-IDF features to classify text reviews as positive or negative. The NLTK library aided in text preprocessing, while scikit-learn facilitated dataset splitting, model training, and evaluation. The model's accuracy and performance were assessed through various metrics such as accuracy score and confusion matrix. This model was then applied to an unlabeled dataset, and the predicted labels were added, resulting in an updated dataset saved as a CSV file.

5 RESULTS

The analysis of fake and real reviews revealed several interesting patterns and differences between the two categories. Fake reviews tend to be shorter, with an average length of around 223.86 characters compared to 536.59 characters for real reviews. Users posting

fake reviews have fewer friends on average (31.82) compared to users posting real reviews (79.36), suggesting a potential connection between limited social connections and fraudulent review activities. Additionally, users posting fake reviews have a lower average review count (19.41) compared to users posting real reviews (140.84), indicating that those with fewer legitimate reviews may be more likely to post fake ones. Surprisingly, fake reviews have a slightly higher average rating (4.23) compared to real reviews (3.91), potentially due to the manipulation of review ratings by malicious entities to appear more credible.

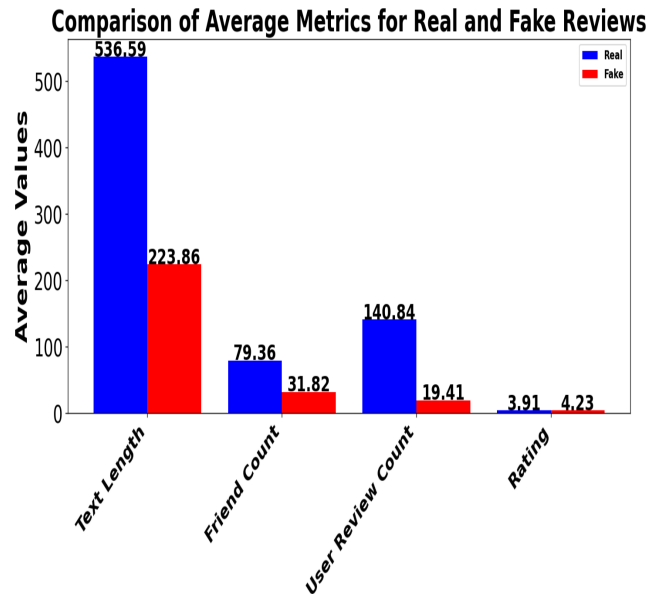


Figure 1: Graph showing main data analysis results.

The developed classification model was evaluated using various performance metrics. The model's accuracy stood at 85.25%, indicating its correct prediction proportion. Precision, at 81.98%, highlighted the accuracy of positive predictions. The recall rate, 88.13%, demonstrated the model's success in capturing actual positive reviews. The F1 score, a blend of precision and recall, reached 84.94%, ideal for balancing trade-offs. The confusion matrix, summarizing results for 348 instances, showed 148 true negatives, 141 true positives, 31 false positives, and 19 false negatives. This assessment underscores the model's balanced performance in identifying positive reviews and minimizing false results.

6 CONCLUSION AND FUTURE WORK

The study assesses a model's effectiveness in identifying fake reviews, finding promise but room for improvement. It notes a somewhat higher rate of false negatives (actual fake reviews classified as real), suggesting potential improvement through model adjustment or data augmentation. Similarly, there are a few false positives, which could be reduced by balanced training data or different feature selection methods.

In summary, the analysis and logistic regression model offer valuable insights for detecting fake reviews. Clear differences between

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C:\Users\5mxz2\Downloads>python test2.py
Accuracy: 0.8525073746312685
Precision: 0.8197674418604651
Recall: 0.88125
F1 Score: 0.8493975903614458
Confusion Matrix: [[148  31]
 [ 19 141]]

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Figure 2: Measures showing logistic regression model results.

fake and real reviews, such as text length, friend count, and review count, could be used as warning signs in automated detection systems. The logistic regression model demonstrates strong accuracy in telling apart fake from real reviews. However, for even better results and to address misclassifications, future research could explore advanced machine learning methods and feature engineering. Integrating external data or natural language processing models might further enhance the system's ability to spot dishonest reviews and uphold online review credibility. This work contributes to spotting fake reviews and aids businesses and consumers in relying on dependable online feedback.

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