Trends of Consumer Behavior Analysis in E-Commerce for Fake/Spam Opinion Detection

[1] **Maysara Mazin Badr Alsaad,** [2] **Prof. Dr. Hiren Joshi**

[1] PhD Scholar in Gujarat University, Department of Computer Science.,[2] Department of Computer Science - Rollwala Computer Centre, Gujarat University, Ahmedabad – 380009, India.

[1] maysara.mazen@gmail.com,[2] hdjoshi@gujaratuniversity.ac.in

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Abstract

User-generated reviews can have a substantial impact on an organization's income in e-commerce. When making a purchase or deciding on a service or product, online customers depend on the opinions of others. Thus, e-commerce product reviews' trustworthiness is critical for organizations, and it can have a direct impact on their reputation and revenue. As a result, some online purchasing and selling companies employ fraudsters to create bogus or fake opinions or reviews on their websites. The objective of fake reviews is to mislead customers into making the wrong purchasing decision. In the last two decades, different methods of detecting fraudulent reviews have been intensively investigated. However, there is still a lack of the literature surveys that can really investigate and summaries the current methods and challenges facing fake opinions detection. In order to tackle this problem, this survey sums up the publicly available datasets and their gathering methods for the detection of fraudulent reviews. It examines the methods that are currently in use for feature engineering for fake review analysis, as well as deep learning and classical machine learning that have been implemented for fake review classification and finds any inconsistencies and limitations.

Keywords: Fake opinion, Spam Review Detection, E-commerce, Deep learning, Machine learning, Fraudsters.

I. INTRODUCTION

Online reviews are an important and inescapable aspect of online purchasing and selling products or services. Consumers' purchasing decisions and the amount of money they spend are heavily influenced by such reviews. Businesses and individuals are actively adopting e-commerce and opinion-sharing websites recently. These websites enable individuals to share their life anecdotes, thoughts, opinions, and emotions about a variety of topics that are including online services, products social, political, and economic. As a result, the number of user-contributed online opinions placed on such websites has risen considerably over the recent years. Such opinions, which are based on users' experiences with certain brands or subjects, have a direct effect on future customer purchasing decisions [1-2]. On the other hand, a huge amount of encouraging reviews entices more consumers for a particular product or trademark. Positive reviews can bring important financial gains for e-business. Correspondingly, negative reviews frequently lead to sales loss [3-4]. Moreover, opinionated posts on social media can be influenced prospective buyers to make or change customers purchasing decisions. As a result, individual consumer reviews are important for making the right selection of the desired products or services. Unfortunately, as e-commerce increasingly developed, the popularity of fake online opinions are immensely increased. These opinions are named bogus/fake reviews. The fraction of fake reviews on e-commerce websites is ranged from 16 % [5], 20 % [6], and 25 % [7] to 33.3 % [8]. Around 10.3 proportion of online products are exposed to review manipulations as earlier as 2012 [9]. Opportunities searching is one of the reasons why people submit fraudulent reviews [8].

For financial benefit, online sellers frequently write favorable fake reviews for their items or bad phony reviews versus opponents' products [10][11]. A historical of fake opinion research is necessary, as it will provide insight into future study possibilities. Despite the existing and current studies, prior researchers have yet to establish a comprehensive definition of fake reviews and provide exact solutions for them to be detected on e-commerce and social media platforms.

For instance, what different categories of fake opinions have been investigated in previous studies? Further, how do we undertake more fascinating research on fake opinion/reviews?. The existing datasets are also restricted, which makes the research on fake reviews limited. In truth, there is very little knowledge available on standard datasets that may be used to detect fraudulent reviews. There is a lack of systematic reviews of fake opinions or reviews in the literature. An uncommon review of misleading information mentions three categories of false information that are fake opinion in e-commerce websites, collaborative system frauds, and fake news in social media. Unfortunately, exclusively researches have focused been on fake opinions detection [12]. The main objective of the present paper is to cover different related literature aspects of fake opinion such as definitions of fake opinion, challenges, features engineering, publicly available datasets, machine learning, and deep learning-based techniques that were applied for fake opinions detection.

II. DEFINITION OF FAKE/SPAM OPINION

Recently, there has been no general acquired definition of "fake opinion," but there have been some attempts to define "fake opinion." Hu et al. (2012) said that fake opinions are when people who aren't customers make online opinions and post them as if they were real customers in order to help people buy and sell online products. For example, these people could be sellers, writers, authors, or any other third-party people. Through this description, fake opinions are particularly used by online merchandisers, like retailers, publishers, and vendors, to get more earnings. Besides, Banerjee and Chua (2017) characterize inauthentic reviews in tourism, such as internet reviews posted by people based on fiction, and consequently, instead of any genuine experience of reaching and staying at a target destination [13]. Hunt (2015) in some alternative ways proposed that fake opinions are untruthful, disingenuous, and misleading discussions in a digital environment. These discussions do not "reveal the honestly believed view of the writers [14].

III. CHALLENGES FOR FAKE/SPAM OPINIONS DETECTION

Truthful reviews are useful to know the client's requirements and reshape the marketing strategies. However, detecting truthful and fake reviews from product reviews is a challenging task. Some challenges are as follows [15]:

a. Due to the use of similar keywords, it is difficult for humans to tell the difference between genuine opinion content and fake opinion content manually.
b. As a result, the opinion content can range from a few sentences to several paragraphs in length.
c. It is difficult to determine whether a reviewer has actually used the product and documented an accurate or fictitious account of their experience with it.
d. There is less attention paid to determining the characteristics of deceptive/fake/spam from different genres.
e. It is difficult to select fake/spam opinion-related features for the detection process based on user preferences.

IV. FEATURE ENGINEERING FOR FAKE/SPAM OPINIONS REVIEWS DETECTION

Fake/spam opinions is a complicated problem because there are no specific features to differentiate between true reviews and fake ones. Regardless, they can negatively influence considerable customers and e-businesses firms. Fake reviewers or spammers are employed individuals whose tasks to write misleading reviews for destroying the reputation of a business or its products; this could produce destruction to the perfection and financial loss of the business [16].

For modeling and classification such reviews, feature engineering is a very important step for extracting strong hints from the texts of the reviews via the development of a classification model. The directions of fake opinions/ reviews detection investigations can be classified into three methods: fake review detection-based reviewer features (behavioral method), fake review detection-based review features (linguistic method), and product-based features. Each method utilizes a set of features such as textual, countable, behavioral of reviewer, rating value, and positional characteristics, which have been implemented for examining and catching fake opinions /reviews in e-commerce fields (Asghar et al, 2019). Figure 1 represents below the literature and variety of feature engineering methods that have been used for fake/spam review detection in the e-commerce domains.

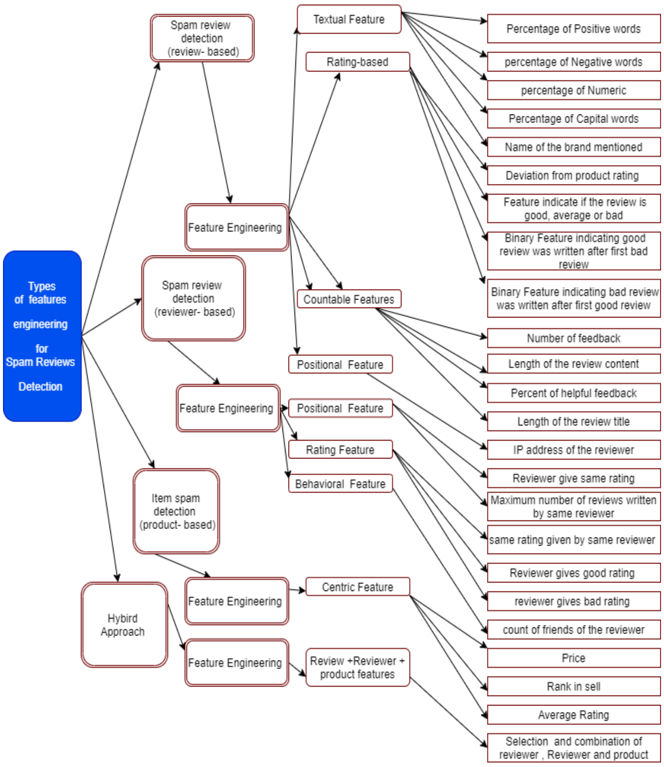

Figure 1: The most used feature engineering method for fake/spam opinion and reviews in e-commerce domain

Online businesses frequently post positive fake opinions and reviews to advertise their products or hurtful fake reviews of their competing companies to reduce sales [10]. These initiatives include using a cashback strategy to encourage consumers to write fake reviews [17] and attempting to manipulate user relationships [18]. Until now, only external behaviors have been employed to explain how frauds and spammers post fake reviews.

V. FAKE/SPAM REVIEWS DATASETS

This section provides the details and descriptions of datasets that have been used for fake opinion detection in prior related research. Using datasets to investigate fake reviews is essential because this is a common practical field of research. There is a limited number of high-quality datasets because identifying fake reviews is a complicated task. There really are three main ways of collecting fake review datasets: The Fakespot website (https://www.fakespot.com/) is a reality-checking system for online reviews that makes it easy to identify fakes. Some previous researchers used human annotators to generate labels for the datasets like "fake" or "truthful" before they could be tested for the detection process. To create a fake review dataset, prior scholars generally used tools like Amazon's Mechanical Turk crowdsourcing. It is possible to learn more about the characteristics of fake reviews by reading the reviews written by the invited participants. However, we are unable to obtain and analyze the features of reviewers. It is also possible to investigate the impact of fake reviews on personal e-commerce behaviors [19, 20]. Furthermore, a fake review dataset can be obtained or downloaded from e-commerce and review sites like Amazon [21, 22] Barnes & Noble [23], and TripAdvisor [24], and Booking.com [25] online travel agencies [26], Booking.com [27], and Yelp [28, 29, 30]. These websites have been widely used to gather fake reviews/opinions datasets. Authors also acquired necessary data from reputable companies or web forums, such as the Xiaomi community (bbs.xiaomi.cn) [31]. As a result, we recommend that more review platforms and existing studies make their review datasets public after removing users' individual traits. Set of public datasets have been employed so far for fake opinion/reviews detection, table 1 below summarizes them for future researchers.

Table 1 Summarization of the existing fake/spam reviews opinions datasets.

Dataset Name	Dataset sources	Dataset descriptions
Amazon datasets	Jindal & Liu (2008) [32] (http://liu.cs.uic.edu/download/data/)	5,838,041 reviews, 1,230,915 products, 2,146,057 reviewers. Collected from 4 product types: Kitchen, (Books, DVDs, Electronic.
	Ni et al (2019) [33], McAuley et al (2015) [34] (https://nijianmo.github.io/amazon/index.html).	142.8 million Reviews about different online products.
TripAdvisor dataset	Ott et al.(2011, 2013) [35, 36] (https://myleott.com/op-spam.html).	1600 hotel reviews including: 800 truthful and 800 fake reviews.
Tripadvisor and Yelp datasets	Li & Ott et al. (2014) [37] (http://web.stanford.edu/~jiweil/data/).	1200 truthful reviews and 1636 fake reviews collected from three fields: doctor, restaurant and hotel.

Yelp Datasets	Mukherjee et al.(2013) (YelpCHI dataset)[38](http://odds.cs.stonybrook.edu/yelpchi-dataset/)	67,395 reviews from 201 hotels and restaurants by 38,063 reviewers
	Rayana and Akoglu.(2015) (YelpNYC. dataset)[39]. (http://odds.cs.stonybrook.edu/yelpnyc-dataset/).	359,052 reviews from 923 restaurants by 160,225 reviewers 608,598 reviews from 5,044 restaurants by 260,277 reviewers.
	Barbado et al.(2019) [40] (To acquire the dataset for research purposes, please write to (o.araque@upm.es).	9456 true and 9456 fake reviews.

VI. FAKE/SPAM REVIEWS OPINIONS DETECTION METHODS

This section introduces critical analysis of the existing machine learning and deep learning based techniques that were used in previous studies for deceptive contents analysis.

A. Fake reviews detection based supervised machine learning techniques

Supervised learning is based on classification techniques in order to identify fake reviews (Ott et al., 2011) [36]. Training and testing datasets are required in these methods. During training, the classifier is fed training data, and during testing, the classifier is fed test data (Li et al., 2014) [37]. Using supervised learning, Jindal et al. (2008) proposed the first model for identifying spam and fake reviews. The authors identify three types of fake reviews that they have identified: fake reviews, brand-specific reviews, and advertisements. They used the supervised logistic regression method to classify duplicate and near-duplicate products reviews as fake or not fake based on the Amazon product review dataset. According to their experimental findings, an AUC of 78% was successfully achieved (area under curve) [32]. Mukherjee et al. (2013) proposed research study for workings of the yelp.com website's applied in it yelp filtering algorithm for fake reviews detection. For the most part, this algorithm is used to distinguish between genuine and fake user reviews. A variety of real-world Yelp.com datasets, including 5678 samples of hotel reviews written by 5124 reviewers and

58517 samples of restaurant reviews composed by 35593 reviewers, were analyzed for the purpose of their experimentation. Textual features like word unigrams, word bigrams, Verb count, Adjectives count, Noun count, and psycholinguistics features were examined in their experiment. They used behavioral features such as the maximum number of reviews written by reviewers per day, the length of reviews, the percentage of positive opinion reviews, and the maximum deviation in ratings when determining ratings. In terms of accuracy, the SVM technique has been tested and found to be 86 percent effective for classification purposes [39].

Shojaee et al. (2013) have derived syntactic and lexical-based attributes from review content. Styleometric is the name given to the attributes used to identify fake hotel reviews on the online TripAdvisor platform. Two classification algorithms, Sequential Minimal Optimization (SMO) and Naive Bays were used as models to evaluate the lexical features separately. According to the experimental results, both the SMO and NB classifiers achieved an f1-score of 81%. In addition; they have improved the accuracy by integrating lexical and syntactic-based features into one set. According to their experiment results, the SMO classifier outperformed the NB classifier and achieved 84% in the same metric [41]. Ott et al. (2013) suggested a framework for detecting deceptive opinion spam relying on hotel deceptive reviews (1600 reviews and reviewers). They used SVM and NB classifiers to complete the classification task, and the experimental results showed that SVM achieved an accuracy of 89 percent using the LIWC tool and bigrams features, while NB achieved an accuracy of 88 percent using bigram features [36].

Using behavioral features such as rate deviation from public ratings, Lim et al. (2010) have developed a method for identifying fake reviewers and spammers. The authors used Amazon's product review dataset to find the rate of deviation for specific products or groups of products in order to conduct their experiments. Finally, they tallied up spamicity of each reviewer's comments [42]. Opinion spam detection based model was suggested by Savage et al. (2015) is based on the abnormal rating value given to the products by the opinion spammers. Reviewers were particularly interested in how public user opinions differed from those based on fake ratings. They also tallied up the reviews' spamicity and honesty. Finally, they utilized the binomial regression method to pinpoint reviewers with rating value distributions that are out of step with the public [16]. According to Li et al. (2014), it is possible to identify fake reviews by defining a general rule. There are 800 fake hotel reviews from the Amazon Mechanical Turk and 400 fake doctor reviews from the clinical experts that have been analyzed for extracting N-grams, psycholinguistics, and Part Of Speech (POS) features retrieved from the text of the review. A combination of generalized additive and topic models was combined with the multiclass classification method known as SAGE (Sparse Additive Generative Model). In addition, the same dataset and characteristics were used for SVM. SAGE and SVM classifications obtained 81% and 78 % accuracy, respectively, in their experiment [37]. For detecting fake reviews, a framework for fake features recognition has been developed by Barbado et al. (2019). They used dataset collected from Yelp.com's for electronic product. In addition, the authors used various supervised machine learning algorithms based on reviewer features (personal, social, review activity, and trust) and review-centric features (sentiment score). Their test results demonstrated that the Adaptive Boost classifier performed best, with an accuracy rate of 82%.[40]. Alsubari et al. (2020) proposed deep computational linguistics features for fake reviews analysis. These features were authenticity, analytical thinking, and part of speech and N-grams. For classification, they applied supervised machine learning algorithms such as SVM, Ada Boost and Random forest. The AdaBoost algorithm obtained the best classification result by achieved 97% accuracy [43]. In [44] another study has been presented for fake reviews detection in e-commerce using 1600 hotel reviews created by Ott et al.(2011). Using different supervised learning methods (RF, NB, SVM), they reached the maximum result of 95% accuracy by the RF classifier.

B. Fake reviews detection based deep learning techniques

One of the most recent advancements in machine learning and artificial intelligence, deep learning which is based on neural networks methods and has led to several technical discoveries around the world. It has also been shown that deep learning can significantly outperform traditional methods in the field of natural language processing [45]. Based on four standard different domains of reviews datasets (21000 Amazon product reviews, 1600 hotel reviews, 200 restaurant reviews, and 556 doctor reviews), Hajek et al. (2020) proposed two neural network techniques: Deep Feed-Forward Neural Network and Convolutional Neural Network for fake review detection using multi-domain datasets. They extracted features from the review text such as specific words and emotions using a lexicon-based method and word embedding using a pertained skip-gram model, which trained on a large corpus of Amazon product reviews dataset. From the analysis of the results of their experimental work, it is observed that the DFNN provided a similar accuracy value of 89 % for hotel and restaurant datasets as well as different values of accuracy that were 86%, 82%, and 82% for doctor and Amazon datasets, respectively. When applying the CNN technique, it has obtained various values of 81%, 87%, 88%, and 89 % accuracy for Amazon, hotels, doctors, and restaurant datasets, respectively. The limitations of their work are that reviewers and product features have not been considered in their work [46]. Ren et al. (2017) to detect fake reviews in in-domain and mix-domain datasets used the GRNN-CNN (gated recurrent neural networks with convolutional neural networks) model. They used a variety of domain datasets, including 432, 720, and 1280 samples each from a doctor, restaurant, and hotel domains respectively. They combined all of these datasets to get more linguistic information and suggested GRNN-CNN model was used to classify the reviews into fake or genuine. The result of their model's predictions 83% accuracy [47]. Zeng et al. (2019) developed a Recurrent Neural Network-Bidirectional Long-short model for the detection of fraudulent reviews. Based on the dataset used in the work of Ren et al. (2017), they split a review text into first sentence, a middle sentence, and an ending sentence were utilized as criteria to divide the review content into three parts. Accuracy rate of 85 %, which was the best result they attained with their method [48]. Using convolutional neural networks (CNN), Li et al. (2017) developed a deep learning model for detecting deceptive spam opinions [49]. Alsubari et al. (2021) proposed hybrid deep learning model based on CNN-BiLSTM neural network for fake reviews detection and classification using different domains datasets such as restaurant, amazon, hotel and yelp reviews[40].

CONCLUSION

Most notable efforts on machine learning based fake review identification were surveyed in this study. To begin, we examined the feature engineering strategies employed by a wide range of scholars. Afterwards, we outlined the currently available datasets and the processes used to create them in more depth. Then, we summarized various standard machine learning techniques and neural network models used for fake reviews detection. Standard machine learning techniques like feature extraction and classifier design help improve text categorization model evaluation. Deep learning, on the other hand, boosts performance by improving the representation learning method, the algorithm's framework, and acquiring new knowledge. Furthermore, we highlighted the recent research limitations and prospective future directions to achieve robust findings in this domain. We may infer that the majority of previous research relied on supervised machine learning in order to identify false customer reviews on Amazon. The problem is that in a fake review detection area, supervised machine learning requires a labelled dataset to forecast if the review is authentic or not. The most often evaluated datasets in the previous works are developed using a crowdsourcing approach, which is difficult to collect tagged datasets.

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