Identifying and Profiling Radical Reviewer Collectives in Digital Product Reviews

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Abstract – Ecommerce sites are flooded with spam reviews and opinions. People are usually hired to impede or promote particular brands by writing extremely negative or positive reviews. It is usually performed in groups. Various studies have been conducted to identify and scan those spam groups. However, there is still a knowledge gap when it comes to detecting groups targeting a brand, instead of products only. In this study, we conducted a systematic review of recent studies related to detection of extremist reviewer groups. Most of the researchers have extracted these groups with a data mining approach over brand similarities so that users are clustered. This study is an attempt to detect spammers with various models tested by various reviewers. This study presents proven conceptual models and algorithms which have been presented in previous studies to compute the spamming level of extremist reviewers in ecommerce sites and online marketplace.

Keywords – *ecommerce, spam reviews, extremist reviewers, spam groups, reviews, spammers, online marketplace*

I. INTRODUCTION

In this day and age, the digital world is flooded by online marketplaces and review portals play a vital role in influencing decision-making of buyers when shopping next time. In this noble cycle, more reviews mean more sales, and more sales means more reviews. More orders also reflect in higher search ranking and sales [1]. There are also higher chances that some reviews are not very trustworthy as they can manipulate decision-making of buyers for their personal benefits. These reviewers act either in groups or individually. Though individual reviewers often write honest reviews due to joy or frustration, they help customers by sharing their own experiences by expressing their overall opinion on any product.

On the other hand, a more alarming situation is when various people form complex opinions. Due to the extremely high number of reviewers, they turn out to be a huge influence on the overall customer sentiments. The level of this influence is not all about spamming reviews. Around 10 to 15 percent of reviews usually echo the previous reviews and improve the influence potential of misleading previous reviews [2].

Every review site should recognize and tackle this activity and take the right steps to prevent and/or identify this phenomenon of large-scale opinion spam. It is one of the most common examples of “collective fraud behavior” in which various users are working together as part of a corporate network to target a specific product. A lot of extremist reviewer groups follow specific techniques to avoid making their collaboration obvious and it is a less popular phenomenon. Since these groups are rewarded financially or in other ways, most of these are operated by an organization and they have multiple targets to spam their common opinions, which usually have common traits to identify. It is possible to use these traits to classify these reviews well with a detailed and strong analysis process. To avoid this behavior, Amazon India came up with a new policy to limit the reviews in a day on a certain product [3].

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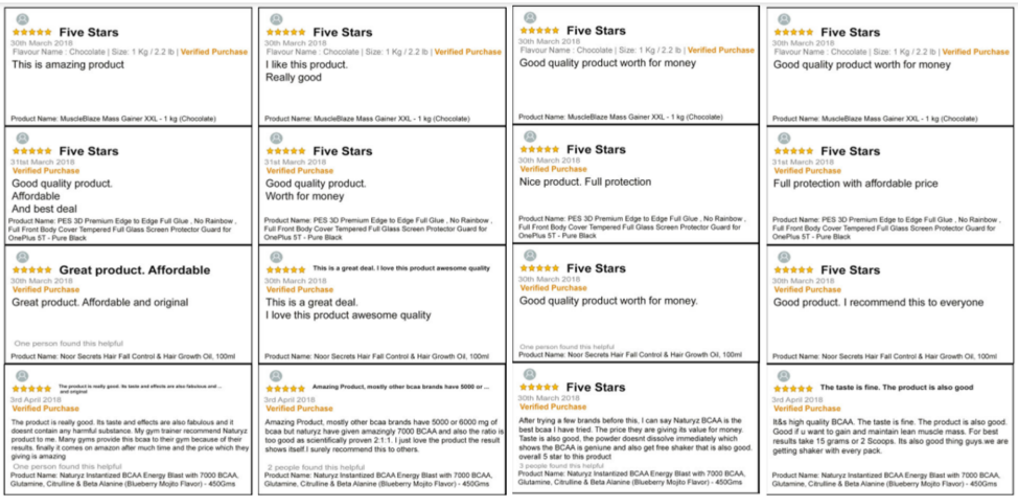

(a) (b) (c) (d)

Fig. 1 – A Sample of Extremist Reviews [14]

In Fig. 1, all the reviews are positive for various brands and have verified signs of purchase on almost similar dates. For example, all reviewers in the first row have posted the review on the same date and left a 5-star rating" having very similar content on the review text. It is one of the common examples of those extremist groups. Rows (a), (b), (c), and (d) belong to the products of 4 different brands. Hence, there are 4 different reviewers on four columns too, who belong to the same group. These reviewers are extremely positive for these brands/products as reflected in their similar comments, extreme ratings, and same date [7]. Hence, this group had extreme sentiments in terms of content and ratings of the review. This type of extremism is aimed to influence consumers' perception for a brand rather than promoting/demoting the product ranking.

II. RELATED WORKS

Online reviews are a very important factor affecting the sales of any product. Customers review their genuine opinion about any brand or product out of their frustration or satisfaction. However, some people are hired to give fake reviews by the brands. There are extremist reviewer groups who leave these reviews. Even though there are several approaches to detect fake reviews, they are limited to identifying those reviews. Naganjaneyulu et al. [15] detected those group reviews as extremist reviews. They used the RNN model to characterize those reviews to train data. TensorFlow's "Recurrent Neural Networks (RNN)" is similar to any "artificial neural network (ANN)" but it has additional memory for calculations. They used various layers like dropout and dense layers, LSTM, and Softmax layer to classify moderate and extremist reviews.

Opinionated social media is widely used by businesses and individuals to make decisions. However, people often manipulate the system for fame or profit by creating fake reviews (opinion spamming) to demote/promote any item. There has been a lot of research in this area for over a decade to detect fake reviewers and reviews. However, a lot of fake reviewers work in groups to target any brand or product by writing bogus reviews in bulk by creating various fake IDs. Lahire [16] conducted a comprehensive and relative study to detect those fake reviewers and reviews with machine learning (ML).

Shah et al. [17] evaluated user sentiments in this age of technology over online product reviews. Leading ecommerce sites in India like Myntra, Flipkart, Amazon, etc. have review sections for every product. Consumers ensure the quality of the product before buying. Products have been polarized by negative, positive, and neutral reviews. This study used machine learning techniques for sentiment analysis. They used various ML approaches like Naïve Bayes, Logistic Regression, and Random Forest to classify feedback. They found Random Forest most accurate for this purpose.

Online reviews have been very important in this day and age due to increasing consumerism. These reviews voice their opinions to be considered when making buying decisions. It has also caused opinion spamming for fame and profits. Rout et al. [18] conducted a study to identify those spammers with big data. They studied a "rating-based model" with large datasets of over "80 million reviews posted by 20 million reviewers through Spark and Hadoop frameworks. They identified Scale effects and mitigated the same for better context. They presented an improved computational framework to compute the spamming level with "exponential smoothing."

People buy products and services online to save time these days. However, these buying decisions are highly influenced by opinions or reviews of customers. Customers

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give feedback to brands to improve the quality of their products and track strategies to boost profits and sales. These reviews are very important for customers to choose the best products. Fake review is a fraudulent practice adopted to degrade or promote products for financial gain. Iqbal et al. [19] proposed an "Ensemble ML model" to identify genuine and fake reviews. They used an Amazon dataset to fulfill this objective. The proposed model performed better than other classifiers." They achieved 99% accuracy with Random Forest.

A. Research Gap

Some groups are targeting brands and spamming reviews on different products for any brand. They took opinion spamming to another level by writing extremely negative or extremely positive reviews deliberately over a brand to demote or promote them. Some researchers have conducted studies to detect those groups [4-6]. But the phenomenon of groups spamming their opinion on a specific brand is largely unexplored. Hence, further studies are needed to track these brand-specific activities as they are violating the code of conduct as they skew the competition negatively for the brand.

B. Objectives

- To discuss review spam analysis techniques tested in recent years
- To explore the proposed rating model and experiments to detect extremist reviews

III. METHODOLOGY

A lot of studies have been conducted on categorizing and detecting online reviews as per user sentiments [11-13]. Reviews have been used widely to augment and develop recommendation algorithms and gather product features [8-10]. Hence, this study is conducted through a literature survey approach to explore various spam analysis techniques and rating models to detect extremist reviewer groups.

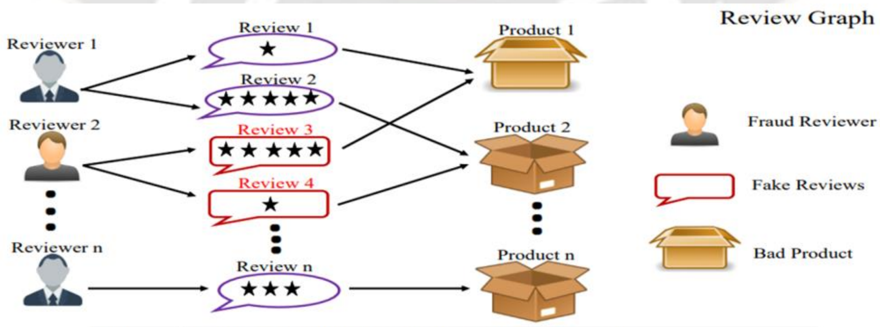
IV. PROPOSED MODEL

User reviews are used to form opinions related to the qualities of specific service or product. Online reviewing has been one of the cornerstones of ecommerce portals. Several websites have been used for reviewing places, products, and attractions like Yelp, Amazon, etc. With the rise in online shopping, a lot of customers depend on reviews to make their buying decisions. It is possible to use online reviews in different ways. Product reviewing is very common on streaming sites like YouTube. Textual reviews are also a very common form of reviewing to influence buying decisions of customers.

A. Review Spam Analysis Techniques tested in Recent Years

Jindal and Liu [20] were the first to introduce "review spam analysis" as they identified various types of spams. A lot of approaches have been discussed in studies to detect fake reviews. Opinion spam could be detected with textual analysis. Identifying fake reviewers and their possible relations have been discussed along with fake review detection. Researchers have also explored graphical approaches and machine learning [4-6]. There is a lack of proper dataset in this field. So, it is not easy to understand the grand reality about those reviews for the common public [7] and fake review datasets have been used by studies.

A lot of these datasets are quite smaller when it comes to size as compared to reviewing systems in the real-world, which have millions of reviews. It has inspired the growth of big data frameworks for the purposes of deployment and study. These systems have been developed widely for social systems and applications overall [11-13]. Big data has been used widely to design reviewing systems and processing. Fig. 2 illustrates the proposed model based on big data to detect extremist reviews by Rout et al [18].



Issues	1: How to identify the reviews from the review graphs? 2: How to deal with large scale datasets?
Purpose	1: Using Rating Model to study large scale datasets with Hadoop and Spark. 2: Identification and Mitigation of scaling effects.

Fig. 2 – Proposed framework to detect extremist reviews [18]

Rout et al. [18] presented a "metadata based modeling based on large-scale reviewing with the help of big data. Fig. 3 briefly illustrates recent trends and contribution to the study [21], such as –

- Analyzing simple "metadata based modeling" over a wide reviewing platform.
- Identifying scaling effects on "Rating Models" and mitigating the same with the application of "exponential smoothing."
- Proposing a "computational framework" for computing the overall reviewer spamicity.
- Using Big Data as a tool to study reviewing systems in the real-world.
- Promoting metadata based model to extend the study by Savage et al [31].

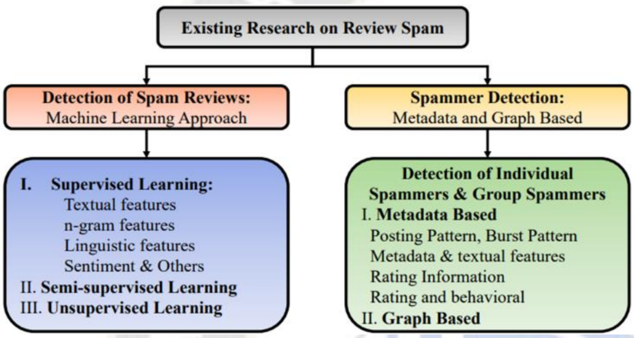


Fig. 3. Recent trends for Extremist Review Detection [31]

Spam detection has been used widely for websites and emails [3,8,22]. Considering these studies, Jindal & Liu [23] discussed the significance and challenges in detecting review spamming. Ott et al. [24] succeeded the same with a synthetic "Gold Standard" dataset of reviews for hotels generated by online workers who remained anonymous. A lot of models are developed for spam detection. There are three perspectives to view this problem – (1) spam review detection; (2) extremist reviewer detection, and (3) detecting groups of extremist reviewers [4,5].

As per the data available for the specific review system, a lot of models can be differentiated as metadata-based or text-based models. Machine learning develops a significant category of approaches applicable in text-based models with linguistic features [25], n-gram features [26], textual features [27], and sentiment [28]. Fig. 4 briefly illustrates existing studies and research on spamming of reviews. Supervised learning is widely used in spam review detection. Because of the lack of annotated and large datasets to represent ground reality, semi-supervised learning approaches [29,30] have been used for review spam detection [23]. Along with these, unsupervised learning has been developed to treat extremist reviews as outliers in "composite feature" domain [27].

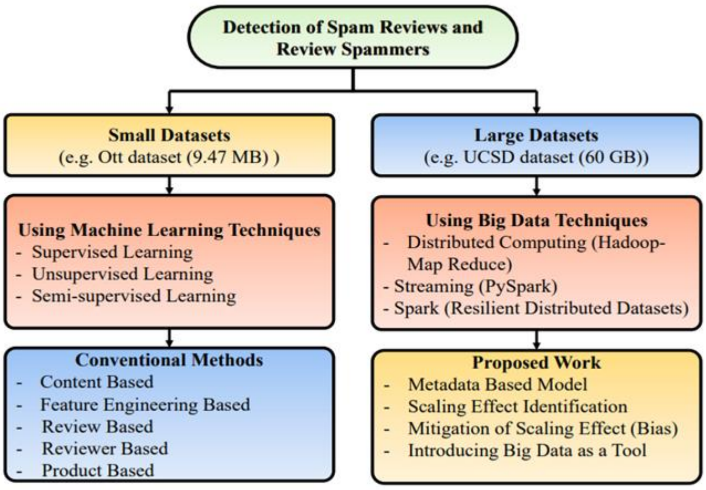


Fig. 4. Related Research on Review Spam Detection [14]

B. Proposed Rating Model and Experiments to Detect Extremist Reviews

When it comes to dealing with challenges related to big data, models are usually relatively cheaper and simple in nature. Considering this reasoning in mind, a simple spam detection model is selected for improvisation and evaluation which is based on rating [21]. It is based on deviations of ratings and reviews to classify a reviewer as genuine or spammer. Since only rating value is used for classification, this model is based on metadata. It has been known to perform better than benchmark systems [33]. This model is majorly used because of its simplicity and versatility [32].

The Base Rating Model is proposed and tested by Savage et al. [31]. The model is used for the calculation and formulation of spamicity of each reviewer. This value is calculated with deviations of ratings given with respect to common opinions for the products. Since rating systems are introduced by the majority of reviewing systems for reviews and that a lot of such ratings are seen to the common public, general consensus is seen about the service or product. Savage et al. [31] claimed that using such ratings for detecting spammers is better than using reviews as a lot of review systems don't have reviews but they use rating systems in different ways. The model is further developed with these axioms –

- In this review system, most of the reviews are shared by honest reviewers. It should be true for any trustworthy review system as negation refers that the concerned review system is totally broken.
- Mean rating refers to the opinion for the product as reviewers are likely to converge in their view of the service/product quality through the ratings [31].

As per these premises, spammers are categorized as entities who attempt to sway the mean rating for the extreme

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ends of the scale of rating for the specific product. It is associated with the demotion or promotion of any product. Hence, spam reviewers can change the existing opinion for the product by sharing ratings which don't align with mean rating and can be identified by evaluating the level of those attempts. If the given opinion is not agreed upon by the reviewer about the products, the reviewer reviews too frequently and is more likely to be identified as a spammer. Disagreement is related to posting reviews lying on the other part of the rating range.

For instance, the rating spectrum on a scale of 1 to 5 is halved at median value of 3. A review with 2 stars refers to disagree with the average rating of 4 as these values are found in various halves of the scale of rating about the median." The probability of a random reviewer is given with binomial distribution when disagreeing with the mean ratings. This probability is used to define the spamicity value. The mathematical expressions and formulations to calculate the model have been presented here. The binomial distribution is defined by the binomial hypothesis function by *P*(). For the "number of trials *n*, *k* trials are ideal, while for the possibility of success *p* and *X* random variable, 1-tailed binomial testing formula is defined in Equation 1."

$$P(X \geq k; n, p) = 1 - \sum_{i=0}^{k-1} \binom{n}{i} p^i (1-p)^{n-i} \tag{1}$$

It is assumed that all the reviews are genuine at the start. Algorithm 1 formally depicts the process. Though the model used is effective for reviews [31], it has a huge drawback when it comes to apply in large reviewing systems. The probability of posting a negative review by a random reviewer is calculated with Equation 2.

$$\phi = \frac{N_d}{N} \tag{1}$$

Another major drawback is calculating the value of *φ*. It is especially the issue with large review systems given the Equation 2. It is because the growth rate of N_d would be a lot less than the value of *N* for a utilitarian and robust review system. Algorithm 1 can fix this probability as it is widely used in the last iteration. Each iteration calculates the weighted mean ratings to smooth the honesty values of reviews and these values must also be considered to update the total disagreeing reviews. Authors at [31] have pointed out the preservation of this data in Algorithm 1.

Algorithm 1 – Proposed Model for Computing Spamicity of Extremist Groups

INPUT: The set of Reviewers, $\mathcal{R}$, the set of reviews $\mathcal{V}$, the set of products $\mathcal{P}$, Δ, $rounds$
OUTPUT: Spamcity values, s, for all reviewers

Set $u_{r,0} = 1.0 \; \forall r \in \mathcal{R}$
$roundCounter = 1$;
while $roundCounter \leq rounds$ **do**
  for each $p \in \mathcal{P}$ **do**
    Compute $\overline{\sigma}_{p,i}$ using Equation 5;
  end for
  for each $r \in \mathcal{R}$ **do**
    Compute $k_{r,i}$ using Equation 6;
    Compute $u_{r,i}$ using Equation 7;
  end for
  if $|u_{r,i-1} - u_{r,i}| < \Delta \; \forall r \in \mathcal{R}$ **then**
    break;
  end if
  $roundCounter++$;
end while
for each $r \in \mathcal{R}$ **do**
  Compute $k_{r,roundCounter}$ using Equation 6;
  Compute $\psi(r)$ using Equation 3;
  Compute $s(r)$ using Equation 4;
end for

V. RESULTS

There is a fair number of extremist groups which reflect on their behavior during classification and labeling. It is a strong sign that extremism is very prominent at the level of brand and groups aim to demote or promote brands because of several reasons which may cover financial benefits either indirectly or directly by the brand. By looking closely at the target brands, it is found that most of them are not that common with a bit of identification among the common public. It goes without saying that brands belong to the startups which might have limited resources for publicity or marketing and may also be involved in unethical practices for fastest growth. In addition, as their customer base is relatively small and has a small number of reviews, extremist reviewer groups may strongly influence their brand image.

There are some reasons these malicious activities don't target reputed brands – (1) They have huge followers and customer base already; (2) Extremist reviewer groups are restricted by a lot of neutral reviews from genuine customers, and (3) They are very popular and reputed to lose if they are engaged in malicious activities. There are premium services offering plans at various costs related to various reviews. A crowdsourcing technique is very prevalent in which products are promoted by a seller with a discount coupon used by the influencer or customer to buy at a lower price and share their opinions.

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They become more reputed on these websites and get a higher amount of discount coupons. Though these reviews have been effective, they don't qualify as verified customers as they get products at lower prices and systems can identify extremist review groups and keep them away by promoting only verified customers' reviews. Hence, those reviewer groups have adopted another strategy. Since 2016, reviews have been restricted in Amazon. So, reviewer groups had to change their mode of operation. Providing cashback/discount coupons is one of the ways to bypass the restrictions on the system. Fig. 5 illustrates an example of a cashback website "cashbackbase.com" in the form of a screenshot of its dashboard [14].

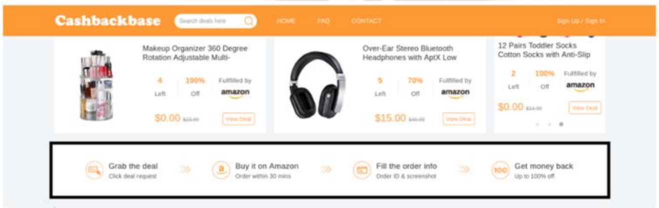

Fig. 5. Dashboard for Cashbackbase.com [14]

In the cashback website mentioned in Fig.5, a reviewer buys a product in the given time limit, claims the discount on the website, and uploads data to prove that they have bought the product on Amazon. Once purchase is verified, a cashback is issued by the website to the buyer's bank account. Hence, the buyer would be rewarded financially for buying the product. Even though the reviews are not mandatory, buyers claim that these websites help gather reviews. Hence, it goes without saying that the online market is flooded with various extremist review sites and instances. It is getting more difficult to differentiate those cases because of their off-site nature. However, it is possible to design feasible and robust systems by categorizing brand-level extremist activities.

VI. CONCLUSION

In a nutshell, it is observed that all of the extremist reviewer groups are engaged in promoting their specific brand rather than demoting any reputed brand. This observation is important because it is more profitable and effective to boost brand image to gain an edge over the competition instead of disrupting the competition as it would need influencing many brands and a lot of time and resources. This study is a novel attempt to initiate the association between extremist review groups and group activities at the brand level to uncover important details. These details would be helpful to come up with better recommendations to use online reviews. Both researchers and ecommerce platforms would be helped by the findings of this study to conduct future studies and detect extremist review groups in online product reviews.

Researchers may use further scope of this study to develop machine learning and deep learning models based on metadata. Simple processes are needed to deal with problems in big data to process huge volumes of data. Textual features and feedback may be used for model improvements to represent prevalent opinion like the ones supplemented by other metadata. It is also possible to apply Graphical Analysis and Machine Learning with Big Data models to categorize review systems accurately.

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