**ONLINE PRODUCT REVIEWS USING AN EFFICIENT DETECTION METHOD OF EXTREMIST REVIEWER GROUPS**

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**ABSTRACT**

Opinionated social media such as product reviews are now widely used by individuals and organizations for their decision making. However, due to the reason of profit or fame, people try to game the system by opinion spamming to promote or demote some target products. When making purchasing decisions, customers increasingly rely on opinions posted on the Internet. Businesses therefore have an incentive to promote their own products or demote competitors’ products by creating positive or negative spam reviews on several platforms. Several researchers have proposed methods and tools to detect review spam automatically. In the proposed system, we collected reviews from the product review site and manually labeled a set of 923 candidate reviewer groups. The groups are extracted using frequent item set mining over brand similarities, such that users are clustered together if they have mutually reviewed products from a lot of brands. To develop a feature-based supervised model to classify candidate groups as extremist entities. Then run multiple classifiers for the task of classifying a group based on the reviews written by the members of that group, to determine if the group shows signs of extremity. A 3-layer Preceptor-based classifier turned out to be the best classifier. Furthermore, note that the proposed technique departs from the traditional supervised learning approach for spam detection because of the inherent nature of the problem, which makes the classic supervised learning approach less effective. Experimental results show that the proposed method outperforms multiple strong baselines, including the state-of-the-art supervised classification, regression, and learning to rank algorithms.

**Keywords :** Opinion Spam, Product Reviews, Rank Algorithms, Fake Reviews

**I. INTRODUCTION**

E-commerce is growing at an unprecedented rate all over the globe. With its growth, the impact of online reviews is increasing day by day. Reviews can influence people's purchasing decisions. Nowadays, reading product reviews before buying the product has become a habit, especially for potential customers. Customers post reviews about a product they purchase, which may be positive or negative. Such reviews provide valuable feedback on these products, which may further be used by potential customers to find the opinions of existing users before deciding to purchase a product. If customers want to buy a product, they usually read reviews from other customers about the current product. If the reviews are mostly positive, there is a good chance that you will buy the product. Otherwise, if the reviews are mostly negative, customers tend to buy other products. While online reviews can be helpful, blind trust in these reviews is dangerous for both the seller and the buyer. Most customers read online reviews before placing any online order. However, the reviews may be deceptive for extra profit or gain, so any purchasing decision based on online reviews must be made carefully. To sell their products, companies often pursue customers to give desired reviews. There is a growing incentive for businesses to solicit and manufacture deceptive reviews, a.k.a. opinion spam—fictitious reviews that have been deliberately written to sound authentic and deceive the reader [1]. For example, OTT [2] has estimated that between 1% and 6% of positive hotel reviews appear to be deceptive, suggesting that some hotels may be posting fake positive reviews in order to hype their own offerings.

**II. OPINON SPAM DETECTION**

It is almost impossible to recognize spam by just reading each individual review because a key difficulty for opinion spam detection is that it is very difficult to manually label duplicate reviews or reviewers for model building [3]. In this case, multiple experts were employed to create a labeled group opinion spammer dataset. This research builds the following primary contributions:

1. It created a labeled group spam dataset. According to our knowledge, this is the main dataset. What was surprising and also encouraging to us was that, unlike judging individual duplicate reviews or reviewers, judging fake reviewer groups were considerably easier due to the group context and their collective behaviors’.
2. It reports a novel relation-based approach to identifying spammer groups. With the labeled dataset, the old approach of supervised learning can be applied [3, 4, and 5]. Although, we show that this approach can be inferior due to the inherent nature of our particular problem:

(i)Traditional learning assumes that individual instances are independent from one another. Although, in such case, groups are clearly dependent of each other, as different groups may share different members. One consequence of this is that if a groupis found to be a spammer group, then the other groups that share members with groupare likely to be spammer groups too. The reverse may also hold.

(ii) It is hard for features used to represent each group in learning to consider each individual member’s on each individual product, i.e., a group can conceal a lot of internal details. This output in heavy data loss and consequently low accuracy. To exploit the relationships between groups, individual members, and products they review, a novel relation-based approach is proposed, which is called GS Rank (Group Spam Rank), to rank candidate groups based on their likelihood of being spammed.

1. A comprehensive evaluation has been conducted to evaluate GS Rank. Experimental results show that it outperforms many strong baselines, including the state-of-the-art learning to rank, supervised classification, and regression algorithms.

**III. RELATED WORK**

Individual fake review detection uses supervised learning, which was introduced in [3] as opinion spam and the problem of detecting reviews. Duplicate reviews are almost certainly fake reviews used as positive training data Different types of abnormal of reviewers were found in [6] . Unexpected class association rules based on a method proposed in [7]. Supervised learning uses [5] employing standard word and part-of-speech (POS) n-gram features. Additional features of supervised learning also used in [4]. To find fake store reviewers, [8] used a graph-based method. A method was proposed in [9] which was distortion-based, but none of them dealt with group spam. Jindal and Liu [10] pioneered the detection of fake reviews.

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Opinion spam and analysed online reviews are introduced in three varieties: untruthful opinions, brand/seller only reviews (no product involved) and non-reviews using near-duplicate content as an indicator of fake reviews. The detection of review-level spam explored linguistic features of text [11], hand-made rules, and combinations of reviewer features. In [11] synthesised fake hotel reviews using Amazon Mechanical Turk, but Jindal and Liu [10] worked on data scraped from Amazon and used content duplicity as ground-truth. A probabilistic framework for the same has also been proposed.

The effect of fraud reviewer groups is more pernicious and subtle than individual fraud reviewers. A group of reviewers instead of individual reviewers addressed the issue of manual labelling. Labelling a group of reviewers, as demonstrated by Mukherjee et al. [12], is less difficult than labelling individual reviewers, as demonstrated by Mukherjee et al. [13]. Studies that leverage metadata to characterise different entities in e-commerce sites can be observed, where products, reviews, and users are classified simultaneously.



**Figure 1: Architecture**

**IV. EXPERIMENTAL EVALUATION**

**A. Algorithm:** GS Rank

The state-of-the-art semi-supervised classification algorithm was included. Rank the groups based on their detect spam by using GS Rank. To calculate the spam city of a review, this assigns the point as 1 for spam, 0.5 for borderline, and 0 for non-spam. To study the feasibility of labelling and the quality of judging, we use the Fleiss’ multi-rater kappa method. The author considers some indicators for spamming activities as below:

(1) Group Time Window (GTW)

(2) Group Deviation (GD)

(3) Group Content Similarity

(4) Group Member Content Similarity (GMCS): (5) Group Early Time Frame (GETF)

(6) Group Size Ratio (GSR)

(7) Group Size (GS)

(8) Group Support Count (GSUP)

All these features or group s are referred to as f1 to f8. When a group attains a feature f > 0, it is a spam group. Also, it is necessary to consider the individual member's as given below.

* Individual Rating Deviation (IRD)
* Individual Content Similarity (ICS)
* Individual Early Time Frame (IETF)
* Individual Member Coupling in a Group (IMC)

Trying to ensure a safe comparison, it compares our method, known as Evidential Group Spammers Detection (EGSD), with two previous works in that the authors rely on the FIM(Frequent Item set Mining)technique to create the candidate groups and almost the same features as in our work. The first method introduced in Detecting Group Review Spam (DGRS) then computed the different indicators' values and used the SVM rank algorithm to rank them. The other method proposed here we focus on the ranking group spam algorithm (GS Rank), which relies on an iterative algorithm to effectively rank the group spammers.

**V. CLASSIFICATION EXPERIMENTS**

Group Spam Features (GSF) is the eight (8) group features proposed. Individual Spammer Features (ISF): A set of features for detecting individual spammers was reported. We represented each group with the average values of all the members of each group using these features. We wish to see whether individual spammer features can also be effective for groups.

Linguistic Features of Reviews (LF): Word and POS (part-of-speech) n-gram features were shown to be effective for detecting individual fake reviews. We want to see if these features are also effective for spam groups. We merged their reviews into one document and represented it with these linguistic features for each group.

**VI. CONCLUSION**

This paper proposes to detect group spammer’s reviews of products. The method first used frequent item set mining to find a set of candidate groups, from which a labelled set of spammer groups was presented. Here we found that even though labelling individual fake reviews or reviewers is hard, labelling groups is significantly easier. Then they proposed several al features derived from collusion among fake reviewers. A novel relation-based model, called GS Rank, was represented, which can consider relationships among groups, individual reviewers, and products they review to detect spammer groups. This spam detection model is distinct from the supervised learning approach. Experimental results showed that GS Rank significantly surpasses the state-of-the-art supervised classification, regression, and learning to rank algorithms.

**VII. FUTURE WORK**

One such confession by an anonymous top reviewer was seen in a blog post. Thus, it is to be expected that the online marketplace will be infested with manipulated extreme review instances.

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