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Giovanni C. Porzio
Carla Rampichini
Chiara Bocci

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Contributed Papers

THE DETECTION OF SPAM BEHAVIOUR IN REVIEW BOMB

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ABSTRACT: In recent years, a new phenomenon called 'Review Bomb' has affected online rating systems. It occurs when a massive amount of accounts reviews a single product, usually negatively to make its reputation slump.
This study analyses the differences among legitimate users and 'review bombers', using common classifiers and techniques from spam detection to identify suspicious reviews, by looking at both content and user's features.

KEYWORDS: review bomb, online ratings, cold start, machine learning.

1 Introduction

Often, before purchasing a product or service, consumers ask for the opinion of their peers who already purchased it. This is commonly referred to as *word-of-mouth* (WOM). A positive opinion among WOM networks is regarded by marketing experts as a valuable and powerful source of reputation for brands. Online rating platforms, or 'review aggregators', are a case of technological innovation for electronic word-of-mouth (eWOM): by browsing a review aggregator, a consumer can read opinions of people who already purchased items (i.e., *evaluands*, such as products, services, place to visits, etc).

Aggregators take this name from the service of recommendation (i.e., a recommender system) they offer. They ask their registered users for submitting a numerical score in a constrained multipoint scale, and then summarise the scores into ratings and rankings (Tomaselli & Cantone, 2020). Scores collected in experimental settings respect methodological assumptions or normality (i.e., independence of observations) but scores collected in online (open) platforms are subject to two biases:

- Purchasing bias, people review what they purchase but they purchase what is already reviewed or, at least, already popular (a case of 'Matthew

Effect');
- Under-reporting bias, people review when they are extremely satisfied or unsatisfied.

The consequence of these biases is a J-shaped distribution of scores in online ratings (Hu *et al.*, 2017; Smironva *et al.*, 2020). These biases make easier to fraud the network of eWOM by injection of fake reviews submitted by the so-called 'sock puppet' accounts. Experimental results confirm that positive fake reviews have an impact on the success of online business (van de Rijt *et al.*, 2014). A consensus on the impact of negative fake reviews has not been reached yet.

Some recommender systems have information if the reviewer purchased the item (e.g., Amazon) but recommender systems generally do not know how much the user is experienced about the item (e.g., how much time spent interacting with that). This issue is related to the fake reviews: one could ask an uninterested friend with an account in the system to rig a review of a item. Should a case like this be considered fake? To overcome such issues, researchers have adopted the broader perspective of 'spam reviews' attack (Hussain *et al.*, 2019). Spam is not necessarily fake but it is an excess of information which is undesired or harmful for the purposes of the system. According to Aggarwal, 2016, a good spam attack, hard to detect, is deployed slowly in the time, so that the sock puppet mimicries the behaviour of a regular user.

Recently, another type of review spam attack has emerged, known as 'Review Bomb', occurring when a massive amount of accounts reviews, usually negatively, attack a single product to make its reputation slump (Tomaselli *et al.*, 2021). During a 'Review Bomb', is often unclear how many accounts are sock puppets and how many accounts are people ideologically driven to review the specific item, but most of them involved lack a history of previous reviews/ratings in the system (*cold-start* problem).

2 Dataset

The dataset includes $N = 59k$ English reviews on the video game *The Last of Us Part II* (TLOU2). TLOU2 was 'review bombed' since its publication date (June 19th, 2020) for ideological reasons (Tomaselli *et al.*, 2021). These reviews were written by registered users on the online platform `metacritic.com`.

From each review, the following metadata are extracted: *i*) username; *ii*) the date the current review was written; *iii*) text of the review; *iv*) score, in a scale

[1:10]; *v*) number of upvotes (i.e., likes) assigned to the review from users, *vi*) number of downvotes (i.e., dislikes) assigned to the review from users; *vii*) number of past ratings that a user provided on Metacritic; *viii*) number of past reviews that a user wrote on metacritic.com. Once collected data, the labelling procedure, consisting of assigning a binary class label whether the review was legitimate (0) or related to the bombing phenomenon (1), is performed.

3 Methods

In the present paper, we propose a methodology for analysing data from a real dataset of TLOU2 reviews, focusing on the online review bomb phenomenon. The data pre-processing stage (data cleaning and handling of missing values) consists of reducing noise words by removing all parts of text which are not relevant for the scope, i.e., punctuation, symbols, and stopwords. Simple Bag-Of-Words and weighted strategy such as Term Frequency-Inverse Document Frequency (TF-IDF) measures are applied to determine term's representativeness. In terms of review's content, some statistical features (e.g., number of punctuation marks, number of unique words, words per sentences) are also extracted.

Techniques for detecting spammer activities on online social networks (Abkenar *et al.*, 2020) and online review platforms (Liu *et al.*, 2017; Harris, 2018) allow to identify accounts involved in review bombing within this dataset. Extra engineered features, therefore, are created to better discriminate not legitimate reviews from legitimate one by looking at users' features, such as username length, username starting with/containing numbers among others.

To reduce the dimensionality of the data and improve the results of the analysis, the most relevant features are selected to enter the model. Popular statistical tests, such as Pearson's test and Chi-squared, are used for this purpose, since they can handle numerical and categorical variables, respectively.

Once got the most important features, these ones are then passed into the classification algorithms to produce a range of models to predict not legitimate reviews. A k-Fold Cross Validation technique is considered to compare different machine learning algorithms ((e.g., Logistic Regression, Naive Bayes, Random Forest, Support Vector Machine); Nematzadeh *et al.*, 2015), generally used in spam (Al-Zoubi *et al.*, 2021) and fake news/reviews detection. Finally, model performance is evaluated by scoring the outcomes from a test set, using precision, accuracy, recall, and F_1 score (Zheng *et al.*, 2015) metrics.

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