THE POLARISING EFFECT OF REVIEW BOMBING

A PREPRINT

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ABSTRACT

This study discusses the ‘Review Bomb’, a phenomenon consisting of a massive attack by groups of Internet users on a website that displays users’ review on products. It gained attention, especially on websites that aggregate numerical ratings.

Although this phenomenon can be considered an example of online misinformation, it differs from conventional ‘spam review’, which happens within larger time spans. In particular, the ‘Bomb’ occurs suddenly and for a short time, because in this way it leverages the notorious problem of cold-start: if reviews are submitted by a lot of fresh new accounts, it makes hard to justify preventative measures.

The present research work is focused on the case of *The Last of Us Part II*, a video game published by Sony, that was the target of the widest phenomenon of ‘Review Bomb’, occurred in June 2020. By performing an observational analysis of a linguistic corpus of English reviews and the features of its users, this study confirms that the ‘Bomb’ was an ideological attack aimed at breaking down the rating system of the platform Metacritic.

Evidence supports that the bombing had the unintended consequence to induce a reaction from users, ending into a consistent polarisation of ratings towards extreme values.

The results not only display the theory of polarity in online reviews, but them also provide insights for the research on the problem of cold-start detection of spam review. In particular, it illustrates the relevance of detecting users discussing contextual elements instead of the product and users with anomalous features.

Keywords  Online reviews · The Last of Us Part II · Polarisation · Cold Start · Spam Review · Online Misinformation

1 Introduction

Before the advent of the Internet, consumers who looked for information on products or brands used to talk about that through conversation with their peers, exchanging positive or negative advice. This is commonly referred as *word-of-mouth* (WOM) and it is a valuable and powerful source of reputation for brands, and of promotion of new products [1][2]. The social networks emerging by the exchanges of WOM may be described as ‘complex adaptive systems’, i.e., systems consisting of heterogeneous entities which interact with each other, generating nonlinear dynamics and collective behaviour on large-scale [3][4].

With the growth of technologies, development of social media platforms, and the shift of marketing into online strategies, the importance of WOM processes increased. Consumers have begun to submit their queries on specific items or brands into online search engines in the same way they would have consulted their peers for an advice. This has allowed the
evolution of WOM into Electronic Word-of-Mouth (eWOM) [5], [6]. Online rating platforms, or ‘review aggregators’ are a case of innovation in eWOM technology. An aggregator collects opinions on items (i.e., *evaluands*: products, services, places, etc.), often in the form of numerical scores in a constrained multipoint scale (i.e., ratings). Therefore, these aggregators provide the public with measures of quality or rankings of items [7].

From a business perspective, positive online reviews help companies earn trust and credibility. Negative or neutral reviews may provide companies with an opportunity to learn about technical failures or new emergent customer needs.

Distribution of scores on review aggregators have typical statistical features (referred as ‘bias’ in literature, too). [8] and the later work [9] demonstrated that the typical shape of the distribution of scores in online reviews is bi-modal and skewed towards an extreme score (‘J-shaped’, see Figure 1). This shape emerges in online aggregators, while in blind experimental studies in product development it does not. Usually in experiments, normal curve emerges instead. Specifically, the difference between observational and experimental scores is the effect of two biases:

- Purchasing bias: people review what they purchase, but they purchase what is already reviewed or at least popular (a case of ‘Matthew Effect’) [10]
- Under-reporting bias: people review when they are extremely satisfied, or unsatisfied [5].

![Figure 1: This figure (courtesy of Hu, Zhang, and Pavlou 2007) shows biases that determine j-shaped distributions, instead of normal distributions, in online reviews.](https://www.metacritic.com/about-metascores)

### 1.1 The Last of Us Part II: a case of Review Bomb

*Metacritic.com* is a review aggregator for movies, TV shows, music, and video games. It allows registered users to assign a personal score or to submit a review (a review is a score plus a textual comment) to any item in its catalogue. Then, it aggregates them into a *User Score* or ‘rating’, which is a measure of central tendency from scores submitted by users in the continuous interval [0,10]. Therefore, observers can get indications of the overall quality of an item in the catalogue looking at its User Score [11]. According to the theory of WOM, negative comments and low ratings can have an impact on how people perceive products or brands, affecting the purchase decisions [12].

On June 19th, 2020, Sony Entertainment released the video game *The Last of Us Part II* (TLOU2). Just a few days after, TLOU2 became the new most user-reviewed video game on Metacritic. During the first days, the User Score floated towards values inferior to 5/10. After 40 days it stabilised around a value of 5.7, after having reached \( \sim 65k \) reviews.

According to journalistic sources [13] that followed that event, the item was ‘bombed’ with an unexpected high amount of reviews in the first days from the release. This was regarded as the widest case of ‘Review Bomb’ (RB) until then. In this context, we can define ‘Review Bomb’ as a jargon expression referring to a phenomenon where a large group of people performs a sabotage of a review aggregator by organising a scheme of mass submission of reviews. This ‘bombing’ swiftly alters the ratings of the item, or its rank. Indeed, RB is noticed when there are short-spanned peaks in
submission of (usually) negative scores, often paired with rude language in the textual comment of the review. Other kinds of online misinformation are deployed over longer times \[14\], instead the explosiveness of the short span is typical of RB. Figure 2 illustrates the popularity of the search query ‘review bomb’ in the last 5 years, showing a spike in searches in June 2020, the release date of TLOU2.

Figure 2: Search trend for ‘review bomb’ on Google between January 1st, 2019 and December 31st, 2020. Courtesy of Google Trends.

It seems that ideology may be the main motivations behind a case of Review Bomb. According to journalistic sources \[13\], the three main cause of the negativity towards reviews in Metacritic were:

- Disappointment for artistic choices regarding the narrative, e.g., the protagonist of the prequel has only a minor role on TLOU2.
- Excessive LGBTQ elements. These were perceived as an attack against the cultural identity of the typical player of video games and also against the more conservative customers.
- More in general the video game was attacked by supporters of #GamerGate, an internet opinion movement that claims that journalistic criticism is rigged by the video game industry \[15\].

It is very plausible that someone even tried to ‘fraud’ the system with strategies like botnets or sock puppetry, i.e. fake accounts controlled by the same person \[16\]. In addition, a system like Metacritic has no information about the actual purchase of the item from casual reviewers (nor has information about the time spent with the item), whereas platforms like Amazon have more personalised information about their users \[17\].

What makes the large amount of reviews in the first days mischievous and less genuine in the look of a reader? Following ‘common sense’, it can be argued that (i) a regular user genuinely angry with a product do the review mostly to punish the producer and to alert further consumers (as displayed in Section 1), while (ii) a ‘negative bomber’ wants to drive a spread of ‘imitating behaviours’, nudging other people (e.g., their friends) to further submit negative WOM into the platform \[18\]. However, there are attested cases of ‘reverse RB’ where there is a push of positive scores into an item, with no intention to boycott it \[19\]. Here the distinction is again between: (iii) users who try to spread a positive WOM about some features of the item and (iv) positive fake reviews, a phenomenon well known where shady businesses can increase the amount of positive reviews through fake reviews, sock puppet accounts, and net-bottling \[20, 21\]. Reverse RB (a.k.a., positive RB) may also emerge as a feedback loop mechanism from (v) people who want to make a peak of positive reviews in order to mitigate the effects of a negative RB. This means that positive bombers may organise themselves to contrast negative bombers, which would lead into ratings which are polarised toward the extreme values of the scale \[22\].

This process can be seen as social polarisation dynamics. Schoenmueller et al. \[23\] demonstrated that polarity in ratings is typical of all review aggregators, with a negative correlation to the history of the user as reviewer (‘veteranity’): veteran users that had reviewed many items, do not make extreme judgments.

2 Theory, assumptions, and research questions

The present is an observational study on a social phenomenon where a large number of reviews is concentrated in a short time span. The first question is: should all users who reviewed a ‘bombed’ item be considered ‘review bombers’? The answer is negative.

2.1 The impossibility of measuring the net impact of Review Bomb

Conceptually, among the users that reviewed the bombed item, there must have been users that would have reviewed the item even an alternative universe where the RB did not happen. We will refer to this conceptual category as regulars.
Those who, instead, submitted a review in the RB but would have not done it in absence of RB, could be considered true ‘bombers’. These categories, while being purely conceptual, lead immediately to some operative questions:

- Question A: How can bombers be detected, or, in other words, who is ‘a bomber’ and who is not?
- Question B: What can be hypothesised about the features associated with being a bomber? In operative terms, what differences should be expected to be observed among the two mutually exclusive sub-populations of the reviews written by bombers and those written by regular reviewers?

Section 1.1 provides an overview of what motivates bombers: they want to enhance social mechanics to drag the rating scores towards an extreme value of the scale. Since both positive and negative bombings are to be expected, it follows that if the population of bombers could be isolated, then a higher polarity in scores (high amount of scores at the extreme values of the scale) is expected among them, too. Other differences between bombers and regulars could emerge in concentration of reviews over time, in the ratio of prevalence of sentiments expressed through scores (e.g., positive vs negative) towards the item, and in textual features.

If existed a tool that, fully detecting a bomber from a regular, would answer to Question A, a further research question commonly raised in technical works like [20] would be:

- Question C: What was the net impact of RB on TLOU2? What would have been the ratings of TLOU2 in that alternative universe where RB did not happen?

We want to demonstrate here that an estimation only on the group of regulars would not answer to Question C. Actually, in absence of quasi-experimental environments, observational methods can not answer precisely to Question C.

According to literature on information cascades [21][24], since RB actually happened, it influenced even the action of regulars. For example, the rating of regular users could have been driven towards an non-central value (overdispersion), because some of them are persuaded to imitate (to 'herd') bombers (e.g., "I realised this video game is worse than I thought after having read other opinions"), or, on the contrary, because some of them reacted to RB by adopting the mirror opposite behaviour (e.g., "I think this video game is middling, however I will rate it positively because I hate review bombers"). This means that an evaluation of net impact of RB on ratings is impossible. As a consequence, the research questions must be more articulated than A, B, and C.

First, to detect neatly bombers from regulars (Question A) could be impossible with observational methods, since, for example, a regular that is persuaded to imitate a negative bomber would end to be undetectable from the last. But also, a regular that wants to contrast a negative bomber may be mistaken for a positive bomber. In terms of observable effects on populations (Question B), we expect that herding would mitigate the differences between the groups, in particular increasing the polarisation among regulars.

### 2.2 Review Bomb as a problem of cold start

The distinction between bombers and regulars is fuzzy, and the research approach can not be on the net impact of RB. However, two peculiar proxy dimensions help to group the population of reviews: legitimacy and veteranity.

Are there reviews that are not legitimate to be counted? The first type of illegitimate reviews are those submitted by sock puppets accounts. These are just fake reviews, as their only purpose is to cheat the amount of 'votes in the count' and to influence other people’s opinions. Even this category is ambiguous. For example, a bomber could ask an uninterested friend to sign up a new account on Metacritic and copy-paste a review. Should a case like this be considered fake? To overcome such issue, alongside fake detection, researchers have adopted the broader perspective of ‘spam reviews’ [25].

A relevant issue in detection of spam reviews is the so-called problem of ‘cold start’: since detection algorithms usually employ information on the history of users (veteranity) to tag their reviews as ‘spam’, users submitting spam in their first review are very hard to be judged. All the information on the likelihood of that review being spam come from the similitude to other spam content[26]. In such cases, algorithms are geared towards a conservative approach: aggregators can not exceed in tagging reviews as spam in absence of robust evidences or just by analogy, because it will make them an hostile environment for new users.

For example, user $u$ who shares an ideological hate for TLOU2 is invited to write a bad review on the video game by a bomber. Arguably, the review from $u$ would be a strong candidate to be tagged as ‘spam’. However, is only reasonable if Metacritic would wait to collect more evidences on $u$ before taking action on the review, because $u$ could become a valuable reviewer in future.

Review aggregators are perfect preys for information bombers. If people want to attack an aggregator through a slow injection of fake reviews on different items with the same few accounts, this would increase over time the likelihood of
being caught in the act. Instead, using new sock puppets or friendly accounts and focusing all the efforts in a coordinated single attack, they hope to drive people to imitate their behaviours triggering a snowball effect (‘domino effect’).

Another type of illegitimate review in the framework of ‘spam’ is the review submitted by someone who lacks commitment in testing the item. For example, people who have not played (or not enough) the video game [17]. Since Metacritic lacks information on the time spent by users in testing the item before reviewing it, and the concept of ‘tested enough’ being fully arbitrary, too, it follows that only clearly fake reviews should be considered illegitimate.

The number of reviews to other items (veteranity) provides an information on the level of commitment of users towards their ‘social role as reviewers’. A fake account that was only aimed at ‘bombing’ TLOU2 is unlikely to have reviewed other items on Metacritic. The relevant distinction in terms of veteranity is therefore between zero and non-zero.

2.3 Research questions

Population of reviews on TLOU2 may be split into two groups:

- G1: reviews from users who only reviewed TLOU2 on Metacritic, plus those ‘illegitimate’ (fakes)
- G2: reviews from users who reviewed other items on Metacritic (non-zero veteranity)

The assumptions are:

1. the statistical populations of G1 and bombers are not identical
2. nor are those of regulars and G2
3. nonetheless the differences in features observed between the populations G1 and G2 are informative about the differences in those features between the populations of bombers and regulars.

This way, the Question B can be answered without the need of a direct answer to question A (see, section 2.1).

Finally, there is also the hypothesis that RB has an influence on regular users. If this can be demonstrated as true, then can be asserted that RB is actually effective (domino effect) as misinformation against the public opinion. This would bridge Review Bomb as the ‘missing link’ between review spam and fake news.

To demonstrate this hypothesis, it is assumed that while regulars may be influenced by RB without mentioning it in the text of their review, all users who express opinions about RB are necessarily influenced by RB. If this sub-group is referred as ‘metatalkers’ (because they talk about what the others are doing and not only about the object of the review), the degree of polarity in scores in metatalkers in G2 can be tested against non-metatalkers in G2. If it is demonstrated that there are significant differences between these two groups, this would increase knowledge about the mechanics of polarisation of opinions and online behaviours. This knowledge would be useful to structure further experimental studies testing theories of social polarisation [27].

Summarising, while the study is aimed to highlight statistical proprieties of many features regarding the RB of TLOU2, the main goals of the study are:

- To identify features associated with suspicious reviews, in the peculiar context of cold-starting reviews (G1). The amount of G1 vs G2 is considered a proxy to estimate the overall gross impact of RB.
- To measure difference in polarity among groups of reviews and its association with veteranity other relevant covariates in G2. Of particular relevance is to test difference in polarity between G2 metatalkers and G2 non-metatalkers.

3 Methodological Section

In order to analyse the behaviour of accounts who submitted a review on TLOU2 and to identify G1 and G2, data is collected as follows:

- a collection on July 7th, 2020, extracting both reviews and information from the accounts of reviewers.
- a re-collection, run 6 months later, i.e., on January 16th, 2021, only on the information from accounts of reviewers.

The reason to collect extra data on months later the release of TLOU2 and the case of RB is that in this way is possible to see if users are still active on Metacritic, or if their contribution was limited to the TLOU2. The number of reviews
submitted by a user (veteranity), in fact, can represent an indicator of how valuable the contribution of the user is within the community, and could be helpful for detection of suspicious accounts.

Section 3 describes how data is collected and how meaningful variables are extracted to capture the behaviour of suspicious reviewers.

### 3.1 Methods of Data Collections

Reviews are collected from Metacritic.com, focusing on the video game TLOU2. Information retrieval of reviews is performed through scraping tools, specifically an R package called `rvest`. An example of review is shown in Figure 3.

Figure 3: An example of review on Metacritic.com. A review includes information on username, user score, publication date, and textual comment.

Table 1 displays the variables that are extracted from the review (Figure 3) and from the user’s account (veteranity/ban).

| Variable   | Description                                                                                           | Type     |
|------------|--------------------------------------------------------------------------------------------------------|----------|
| Username   | ID of the reviewer                                                                                    | String   |
| Day        | Day of submission of the review                                                                       | Date     |
| Text       | Comment of the review                                                                                 | String   |
| Score      | A value submitted by the user to TLOU2 in the range [0, 10]                                            | Integer  |
| Veteranity | Number of historical reviews submitted by a user on Metacritic before January 16th, 2021             | Count    |
| Ban        | It indicates if a user’s page does not exist anymore at point in time selected, i.e., January 16th, 2021 | Binary   |

The variable ‘Ban’ classifies accounts existing in July, but not in January. There are several reasons why a user might not exist in January (or, in general, after a while). It is more likely that the account was removed by Metacritic rather than self-deleted, due to Metacritic’s terms on cancellation. These banned users are the ‘illegitimate’ component of G1.

### 3.2 Language detection

To label and filter the reviews by language, we used Python, specifically its libraries `langdetect` and `Google Translate API`, which include auto language detection.

Reviews may be written in any language. Variability in the count of reviews and in the average of scores per groups of languages are informative about general attitude of people who write about the product in those languages. However, with the aim to keep coherence and robustness in results, the analyses that will answer to research question from Section 2 will focus on the corpus of reviews in English. An example that clarifies this choice is the analysis of variance in Lexical Diversity (LD) among different groups of reviews, or over time. LD is the number of unique word in a document (e.g., a single review) [28]. LD is highly influenced by the grammar structure of the language, hence the choice to focus only on one languages to keep the estimator of LD coherent and unbiased. English corpus is expected to be the widest.

### 3.3 Aggregation of days into phases

In the data collected in Section 2.1, the time variable is expressed in 40 intervals of days. Since most of reviews were submitted in the first days, to contrast overdispersion the daily intervals in the time variable can be aggregated in fewer intervals loaded of about the same load of reviews. Specifically, the empirical distribution of reviews per days is split
into the quantiles of its empirical cumulative empirical distribution function (ECDF). Being the time variable expressed in days, quantiles of ECDF are the days that approximate thresholds of the cumulative amount of review until the end of that day. This approach, however, has a pragmatic issue: when the load of daily reviews is strongly skewed towards one or few days (overdispersion), quantiles have a non-trivial absolute error; therefore, only configurations with low number of quantiles are truly effective to aggregate days into phases of (theoretical) equal size.

In order to control the error are employed Chi-Squared statistics against the null hypothesis of exact same amount of load of reviews among phases. Another established measure to evaluate inequality among classes is the Gini index.

### 3.4 Aggregation of scores into sentiment

Reviews in Metacritic have already an aggregation scheme of scores in three colours, indicating the sentiment of the reviews towards the item (Table 2.)

| Score range | Sentiment | Colour |
|-------------|-----------|--------|
| [0, 4)      | Negative  | Red    |
| [5, 7]      | Neutral   | Yellow |
| [8, 10]     | Positive  | Green  |

We also aggregated scores in a similar fashion as in Table 2, from three (negative, neutral, positive) to five (Very Bad, Bad, Neutral, Good, Very Good) categories (Table 3.) In this way, a score equal to 6 higher than +5, the review considered a positive review;

However, this scheme does not account anomalous behaviours typical in RB: users that only want to push a bad rating to a product will only rate it 0 or 1, while those who want to raise the ratings will rate the product as a 10. The proposed scheme accounting for this issue is displayed in Table 3.

| Score range | Sentiment |
|-------------|-----------|
| [0, 1]      | Very Bad  |
| [2, 4]      | Bad       |
| [5, 7]      | Neutral   |
| [8, 9]      | Good      |
| 10          | Very Good |

### 3.5 Identification of Topics

In order to assign reviews into topic of discussion the English corpus is pre-processed: all characters are low-cased, stopwords are removed, words are lemmatised (e.g, 'worse' is lemmatised in 'bad') and then stemmed (i.e., reducted to root). Pre-processing was done with R packages tidytext and tm.

In Section 2 emerged the necessity to quantify the amount of users ‘metatalking’. In Section 1, it is also reported that politics and the topic of LGTBQ played an important role as triggers of RB.

The typical length of the reviews is short (max. 5500 characters) and usually, is very informally written. There is mild consensus among experts that advanced methods of unsupervised topic modeling techniques do not perform very well in topic modeling of short documents (e.g., reviews, but also tweets or comments in forums or social media) [29].

The reliable (but time expending) technique to assign a topic to documents falls under the methodology of 'Bags of Words': reviews are considered as set of pre-processed words and topics are assigned through a list (dictionary) of words and tokens (textual patterns). If at least one of the words or tokens in the review is in the dictionary, the entire reviews is labeled with that topic. By construction, it follows that topics are not mutually exclusive. For example, the interpretation of a review that is labelled 'True' for both "Political" and "LGTBQ" may be that the user who wrote it mentioned a politics, and LGBTQ as separate issues, or that he or she expressed the reference to LGBTQ in relation of a political issue.

This method lacks a recognition of the absolute frequency of words, since any non-zero frequency is accepted as relevant to the topic. However, since the reviews are very short, the expected frequency of a word in a review is ~0, hence the assumption that any non-zero frequency of a keyword is relevant for the topic fits well the purpose of text mining on short texts.
Specifically, this inference process is subject to Type I error, when a reader notices that a review labeled to a topic actually do not mention that topic, while it is subject to Type II error, when a reader notices that a review mention a topic, but is not labeled with that topic. The wider the length of a dictionary, the higher is the prevalence of Type I errors and the lower is the prevalence of Type II errors [30].

The following examples of such errors explain red reason why this method is fit for further analysis of statistical features in groups of reviews.

- Example of text in Type I situation: "This video game has the potential to trump any competitor!". The word "trump" usually refers to a politician, but in this case is a jargon to say 'outdo'.
- Example of text in Type II situation: "Donald Dumb hates this video game!". Here the user is referencing the politician, but since the surname is caricatured into a joke and the keyword absent in the dictionary, the reference is not caught.

The absence of "dumb" from the dictionary of politics in the example is not an error, since under normal circumstances it is not associated to politics. The notion of token here comes in help, because if "Donald" and "Dumb" are ambiguous, respectively, there is no doubt that the token "Donald Dumb" is a keyword reference to the politician. However, unless it does not recur frequently as a jargon (like, 'woke'), this Type II error is trivial.

Since the relevance of a Type II error is tied to its frequency in the corpus, while building up dictionaries is important to be sure to add those words that are more frequent in the corpus without being very ambiguous in meaning [30]. To achieve this result, the construction of dictionary can be carried out in two steps:

- To begin, a priori recognition of non-ambiguous keywords.
- Iteratively, until the result is satisfying, a posteriori observation of the most frequent words only in those reviews with the label set on 'False', to add more keywords in the dictionary that were previously excluded.

This is the most efficient way to avoid Type II errors without raising Type I errors.

Table 4 summarises some variables mentioned from subsection 3.2 to 3.5.

Table 4: Secondary information.

| Variable       | Section | Description                                                                 | Type     |
|----------------|---------|-----------------------------------------------------------------------------|----------|
| Language       | 3.2     | Inferred language of the Text. The study is focused on English language.     | Categorical |
| Lexical Diversity (LD) | 3.2 | Number of unique unigrams ('words') in the Text.                             | Count    |
| Phase          | 3.2     | Smaller intervals of time, all loaded with similar amounts of reviews       | Ordinal  |
| Rating Sentiment | 3.4   | Five ordinal classes of sentiment: Very Bad, Bad, Neutral, Good, Very Good.  | Ordinal  |
| Metatalk       | 3.5     | The review mentions 'Review Bomb' or similar concepts                       | Binary   |
| Politics       | 3.5     | The review mentions politics                                                 | Binary   |
| LGBTQ          | 3.5     | The review mentions Lesbian, Gay, Bisexual, Transsexual and Queer topics     | Binary   |

3.6 Measure of polarity

Polarisation is a terminology originated in natural sciences that lately has been adopted in social sciences. A shared technical definition of polarisation is not reach in social science. The proposed definition is: a population is polarised when in the past was it observed as distributed with a concave function (possibly around a central value), but in a second observation it is distributed with a convex (or bi-polar, or bi-modal) function. In other terms, the density or mass of the distribution shifted from the central value towards two values at the extreme of the original distribution.

The typical example of polarisation in social sciences is the political polarisation, which is a shift of moderate electorate towards two extreme positions. For example, it can be observed an increase in both people who self-identifies as Democrat voters and in people who self-identifies as Republican voters, with a decrease in people who do not self-identify with a political party [27]. By extension, sometimes in social sciences the term 'polarisation' is invoked regarding any process where is observed a change of sign from + to - in the kurtosis of a variable, even in absence of the emergence of two poles or two local modes in the distribution.
In statistical modeling of social phenomena, bi-modal data are analyzed as a particular case of Mixture Models: models which assumed that the empirical observations are sampled from more than one population. A very successful family of Mixture Model for analysis of skewness and overdispersion in count data is the Zero-inflated Model for counts \[31\].

Ratings are expressed on scales which are constrained and finite, therefore by the standard model should be a mixture of Beta-binomial distributions \[32\]. In the case of the J-shaped distribution in cases of RB, each Beta-binomial distributions would model a sub-population of raters, with at least two distributions degenerating towards the extreme values, which represent 'bombers': people who, no matter what, will always rate the item with maximum or minimum score. A simpler alternative would be to adopt a single Beta-Binomial with \(\alpha < 1\) and \(\beta < 1\).

While the specification of the model may be hardly determined among alternatives, the estimation of polarity in the sample for constrained data (e.g., distribution of scores of rating) is straightforward. The generalisation of the measure in \[23\] is:

\[
Polarity(X) = \frac{n(x = \min(M)) + n(x = \max(M))}{N}
\]  

(1)

where \(X\) is a distribution of rating scores and \(M\) is the scale of measurement.

This measure has only some minor problems in interpretation of \(Polarity(X)\). For example, a case where half of the sample degenerates towards \(\max(M)\), \(Polarity > 0.5\), which according to \[23\] would result in detection of a polar distribution even in absence of a second local mode in the values. This is the reason why authors of \[23\] pair Equation 1 with other measures of location and skewness. Aside these stress-cases, Equation 1 is a robust measure of overdispersion in J-shaped distributions.

Since Equation 1 measures polarity of a distribution, the time derivative of it measures polarisation. Adopting the discrete approach of the time variable in 3.3 allows to measure the process of polarisation as the net differences of polarity between subsequent phases. Differences in polarity may be employed to measure differences among groups, too.

In section 3.4 scores were aggregated into rating sentiments. The difference in measuring polarity on sentiments (instead of scores) is only in regards of \(n(x = 1)\) would be added to \(n(x = 0)\) as minimum values of the scale. Again, the assumption here is that users perceived 1 as the minimum value of the scale even in presence of 0 (likely, not detecting 0 as an option).

### 4 Results

#### 4.1 Statistics on Languages

Python’s algorithms detected more than 20 different languages, even if the majority of them had a trivial weight in the the corpus, and 78% of them were written in English. In Table 5 languages with less than 250 reviews are conveniently grouped according geographical and cultural associations (e.g., religion). Some reviews consisted only of symbols (for example, emoticons) and were grouped into “Others”.

| Languages                              | Number of reviews (n) | Average Score |
|----------------------------------------|-----------------------|---------------|
| English                                | 51,120                | 5.0           |
| Spanish                                | 5,882                 | 6.1           |
| Russian, Greek and Slavics             | 3,419                 | 6.0           |
| Portuguese                             | 3,408                 | 7.3           |
| Chinese, Japanese, Korean and Other Asians | 351                   | 3.0           |
| Italian                                | 340                   | 8.3           |
| German, Baltics and Nordics            | 284                   | 8.0           |
| French                                 | 275                   | 7.6           |
| Arabic, Farsi and Turkish              | 260                   | 5.3           |
| Others and only symbols                | 127                   | 4.7           |
Since majority of users wrote the review in English, the meaning of the inference on the Average Scores must be conceptually limited only on the population of users who refused to or cannot write in English. It is assumed that in this sub-population can be over represented kids and people with low education. At the same time, not all the people who wrote the review in English speak it as first language.

Given also difference in the number of reviews, a wide difference was not observed in the average reception of TLOU2 among west European languages speakers (e.g., Italian vs. German). However, differences emerges between Europeans, Asians, and speakers of languages of country where majority of people follows Islam (Arabia, Iran, Turkey, etc.). This result may be not conclusive on the matter since it lacks counterfactual data for controlling for the expected (or ‘prior’) score of such groups. For example, it is not known if Asian-speakers display a tendency towards lower scores. However, in literature an average score of 3/10 would still be regarded as very low.

### 4.2 Sentiment through time

The time distribution of reviews is skewed towards first days: the value actually decays over time (Fig. 4). 11.5% of ECDF is reached before the end of the 1st day, 22% before the end of the 2nd day and 31% before the end of 3rd day. Such empirical distribution left open configurations in: (i) 3 phases of \( \sim 33.3\% \), (ii) 4 phases of \( \sim 25\% \), (iii) 5 phases of \( \sim 20\% \), (iv) 9 phases of \( \sim 11.1\% \), or (v) 10 phases of \( \sim 10\% \). Any other configuration imposes percentages that diverges too much from the ECDF.

Table 6 displays the Chi-Squared error of the proposed configurations.

| Number of Phases | Chi-Squared | \( p \)-value | Gini |
|------------------|-------------|---------------|------|
| 3                | 179.2       | \(< .01\)     | 0.03 |
| 4                | 298.6       | \(< .01\)     | 0.041|
| 5                | 279.4       | \(< .01\)     | 0.041|
| 9                | 738.2       | \(< .01\)     | 0.068|
| 10               | 693.9       | \(< .01\)     | 0.066|

All the five configurations in the phases would reject the null hypothesis of assumption of homogeneous distribution, which is interpreted as that no configuration approximates the theoretical perfect equality in the amount of review per phase. However, Gini values can be interpreted as very low for all the configurations meaning that in all cases the relative error in the distribution of the load of the covariate is very small. The difference in Chi-Squared statistics in configurations with 9 and 10 phases leads to exclude adoption of these cases. While a lower Chi-squared statistics is desirable, an higher number of Phases is more insightful to visualise and analyse the time dynamics of covariates, therefore 5 Phases seems a good compromise (Table 7).

Figure 4 displays the Rating Sentiment increasing over time, with Rating = 10 overcoming Rating = 0 as the mode in Phase 3. Figure 5 displays the consequent inversion of the J-shape.

### 4.3 Topics

Three dictionaries (Table 8) were built up on the topics of metatalking, politics and LGBTQ:

To make clearer the iterative process of build up of dictionaries, some odd words are discussed. Among the oddest \textit{a posteriori} keywords, both “jedi” (305 reviews in the English corpus) and ‘star war-’ (298 reviews) refer to a specific movie, namely Star Wars: the Last Jedi. Many users pointed out similitude not between the TLOU2 and the movie, but
Figure 4: Comparison of rating sentiments trending in absolute values in the 40 days with ratings scores trending in relative values in the 5 phases.

Figure 5: A better overlook about the inversion of polarity in ratings scores from Phase 1 to Phase 5

between the criticisms about the two items. Another odd word, ‘xbox’ (236 reviews) is absent from any dictionary. It refers to a competitor product and it was typical of negative reviews suggesting to shift to competitors. These cases were not regarded as metatalk but as ordinary talk in eWOM. Instead, ‘anita’ (256 reviews) refers to Anita Sarkeesian, a video game critic. This keyword was associated to political criticism because of Sarkeesian being a target of the #GamerGate campaign. Other keywords were misspelled versions (e.g., propoganda for propaganda), while others were strongly rooted in niches of political jargon (‘npc’, 206 reviews; ’sjw’, 1345 reviews; etc.).

It can not be excluded that keywords have been undetected in the process. Nevertheless the relative low frequency of undetected keywords (expected to be less than 100 reviews per undetected word) ensures that the error should be small.

In Table 9 are reported statistics on the three topics. Users who interpreted the case of TLOU2 as an occasion to talk about politics, typically display negative sentiments towards the video game. This effect is mitigated for users who discussed about the exposure of the topic of LGTBQ. On the other hand metatalkers display a better sentiment towards the video game.

Figure 6 displays how rating sentiments trended in the five phases. The histograms with the black edge display sentiments among the reviews discussing the topic, and histograms with the grey edge display sentiments among
Table 8: Dictionaries.

| METATALK          | Dictionary                  |
|-------------------|-----------------------------|
| A priori          | bomb-, boycot-, controvers-, critici-, critics, fake, journalis-, metacritic, rati-, sabotag-, scor-, streamer-, troll- |
| Observed in corpus| 19th, are mad, balanc-, bandwag-, bias-, blind-, bots, bottin-, brigad-, comment-, communit-, complain-, critiq-, crybab-, divisiv-, downvot-, first day, grade-, hater-, ignore the, immature, incel-, jedi, moron-, overreact-, people who, polar-, salty, statistic-, star war-, the 0-, user’- who hate |

| POLITICS          | Dictionary                  |
|-------------------|-----------------------------|
| A priori          | agenda, alt right, alright, cancel cult, cancell-, conservative, democra-, far left far left, far right, fascis-, feminis, gamergate, ideol-, jew, kike, leftis-, nazi, nazis-, politic, progressive, propagand-, racis-, shill, sjw, social justice warrior, virtue sign- |
| Observed in corpus| activis-, alt-right, anita, asia-, far-right, feminaz-, freedom of, globohomo, ideolog-, ideolog-, ideolog-, lectur-, moral-, polical, propogan-, religio-, retocon, socialis-, sponsor-, trump, white man, white men, woke |

| LGTBQ             | Dictionary                  |
|-------------------|-----------------------------|
| A priori          | -gender, bisex-, dyke, fag, faggot-, gay, gender-, heterosexual, homophobi-, homosexual, intersex-, lesb-, lgbt-, non-binary, nonbinary, pansexual, queer-, tran- |
| Observed in corpus| androge-, cis, degenerate, dyke, erotic-, feminin-, hetero, homo, homopho-, homophon-, hulk, inclusi-, kiss-, lgbt, lezb-, lezz-, masculin-, pedo-, porn-, same sex, sex scene, shemale, sodom-, stereotyp-, taboo |

Table 9: Statistics on Topics.

| Topic  | n   | Avg. Score |
|--------|-----|------------|
| Metatalk | 13,283 | 6.4       |
| Politics | 7,347  | 3.06      |
| LGTBQ   | 7,305 | 4.65       |
| Labeled | 20,406 | 5.11      |
| Unlabeled | 30,714 | 4.99      |

reviews not discussing the topic. Values are relative to the maximum value reached by the group in one of the five phases. The figure allows, therefore, to compare the relative load of the sentiment on the whole histogram, but not the absolute values of the groups (see Table 9). Among metatalkers, the sentiment “Very Good” has always a higher relative frequency than in non-metatalkers. Hence, the average score in Table 9 is overall constant over time, even if the amount of reviews referencing metatalk slightly increased in latter phases. Noteworthy is the decline over time of Politics, with a flip of sentiments towards the latter phases: most of ‘negative bomb’ among political talkers happened in the first two phases (the first four days).

4.4 Veteranity, spam, and polarity

In Section 2, it was assessed that, in order to carry out an analysis of polarity (Section 3.6), two groups, G1 and G2, should be isolated. Table 10 confirms the hypothesis that G2 displays a lower polarity than G1.

Is this result robust all along the dimension of veteranity? There are only 10,552 reviews (21% of the English corpus) in G2. Figure 7 confirms that the amount of reviews (n) of TLOU2 decays with a power law at the increase of the threshold of veteranity: it diverges from log-linearity, decaying faster before 10. Average score increases linearly ($R^2 = .3$) along veteranity.

Polarity displays a convex behaviour: it decreases until the threshold is >27. This means that it decreases for 10324 users, 97.8% of G2, which is all the cumulative density of the Empirical Survival Log Function in Table 7 before >27. After this threshold, it stabilises around 0.5.
Figure 6: Sentiments in the topics trending over time.

Table 10: Statistics on groups based on activity on Metacritic.

| Group | Component | n   | Avg. Score | Polarity |
|-------|-----------|-----|------------|----------|
| G1    |           | 40,568 | 5.15       | 0.722    |
|       | One Review| 40,464 | 5.16       | 0.722    |
|       | Ban       | 104  | 2.18       | 0.75     |
| G2    |           | 10,552 | 4.63       | 0.636    |

The amount (104) of the Ban components of G1 is very small compared to the total size of English corpus (51,120) and to the total size of G1 itself (40,568). This confirms the assumption in Section 2 that, while Metacritic likely employed a system to detect illegitimate bombers, it failed to spot spam among G1 due both the problem of cold-start [26] and the incentives to not ban new users (Section 2).

In the English corpus there are at least 1,722 suspicious or low-effort cases that are good candidates to be tagged as sock puppets. These are detected through typical features:

- high-similarity among two or more usernames (e.g., "david2000" and "davvid2000").
- username made only of numbers (e.g., "221000000").
- the same character is repeated more than 4 times in a row in the username (e.g, "user1111"; "daaaaavid").
- high-similarity in the review.
- the same token is repeated more than 2 times in a review (e.g., "this game is horrible horrible horrible").
- the same character is repeated more than 3 times in a row in a review (e.g., "aaaaaah this game is horrible").

Table 11 displays how polarity decreased along the 5 phases. For a visual support of the inversion of the 'poles' of the J-shape, see Figure 5.

Finally, Table 12 displays polarity among the topics. While polarity is always lower in the topics (with arguably an exception for Politics), we would expected that metatalkers displayed more polarity in the G2 group, as a form of reaction against the object of their ‘meta’ talk: the RB itself. Observations contradict this hypothesis. However, there is a strong imbalance between the $n$ in metatalkers and not metatalkers in G2: the ratio is slightly over near 1:3 both in the whole corpus and in G2.

An explanation for this imbalance is that metatalkers were just no more than 34% of the users who approached Metacritic to review TLOU2. However, as a consequence of the higher likelihood to contain a keyword due to a higher number of word in the review, the Bags of Words methods are always biased towards labeling as feature $= T$ (see, Section 3.5).
Could the number of words be a factor of confounding in the assessment if non-metatalkers truly adopt a more polar rating than metatalkers? This doubt is discussed in the following subsection (Section 4.5).
4.5 Lexical Diversity

Lexical Diversity (LD) is the number of unique words in a document. As argued in [28], LD is the best and most robust measure of length of a document. For example, in the English corpus, LD and the number of characters per review have an almost perfect mutual information ($R^2 = 0.96$). There were cases where users repeat slogans, usually made of offensive or nonsense words. This behaviour may be due to a rule in Metacritic: a review with less than 75 characters cannot be submitted. Therefore some users filled the reviews with copy-pasted slogans to reach the threshold of 75 characters. 1,570 cases of this behaviour can be identified filtering for reviews with LD < 10.

Figure 8 displays the survival function of cases over the increase of threshold of LD, expressed in logarithmic scale. The decay is exponential, with a final tail (>380) which decays very quickly. This is likely due to the low amount of cases (less than 1000) but no insight is discussed in the present analysis because more investigations are required in different research fields.

![Figure 8: Empirical Survival Log Function over Lexical Diversity (LD).](image)

In Figure 9 it can be noticed that a lower LD is associated to both the extreme sentiments and Metatalk = T, therefore LD must be a confounding factor in assessment of polarisation in metatalkers, as supposed in previous Section 4.4. More in general, topics show higher degree of LD, as expected. Peculiarly, the distribution of LD among Sentiments in Figure 9 looks like a symmetric pyramid.

If, to make an example, the subset of cases in G2 is restricted to only reviews with LD > 30, then there are:

- a group of 2,466 metatalkers in G2 with a polarity equal to 0.556.
- a group of 4,212 non-metatalkers in G2 with a polarity equal to 0.551.

At this threshold of LD the two groups show equivalent polarity. To illustrate further this point, when the threshold is raised to LD > 65, there are:

- a group of 1,727 metatalkers in G2 with a polarity equal to 0.484.
- a group of 1,744 non-metatalkers in G2 with a polarity equal to 0.446.

Hence, controlling for LD, it is found that veterans metatalkers - users with a high amount of reviews on Metacritic mentioning the context of RB - were more influenced towards polarising their opinion more than veteran non-metatalkers.

5 Conclusions

This is an observational case study on one of the widest case of Review Bomb, which is a unexpected extreme peak of reviews in a very short time span, plausibly achieved through effective techniques of ‘spam’ (e.g., sock puppets accounts). The results display that the motivation behind the ‘bombing’ is ideologically driven, makings this case study of particular relevance about its technical aspects and issues in social sciences.
The methodology of research employed techniques of data aggregation and visualisation to provide insightful descriptions of the evolution of the phenomenon in the first 40 days. Textual features were extracted with Bag of Words techniques.

While the study regarded the RB about the video game ‘The Last of Us Part II’ on the review aggregator Metacritic, most of the knowledge gained from this research can be generalised for any case of information bombing. In particular, it emerged that the two relevant tasks in researching misinformation/information spam in online reviews are:

- detection of ‘bombers’: these are users that want to manipulate the public perception of a product. In this case they did it with a mass distortion of the ratings exploiting the weakness of detection systems known as ‘cold start’. Metacritic likely spotted only very few of them. Evidence suggests that anomalies in the textual content and in the usernames may be key elements in detection of fake reviews/review spam in cold starts;
- detection of those regular users that were influenced by ‘bombers’. The judgement of these users over the product has been altered: some of the regular users herded the peaking crowd of distorted bombing opinions, others reacted by adopting a rating aimed at contrasting the ‘bombers’, behaving themselves as ‘bombers’, too.

The combined effects of ‘bombers’ and altered regulars are monitored across time and other variables through net differences of polarity (frequency of extreme sentiments, e.g., ”Very Good” / ”Very Bad”). It is demonstrated that polarity was negatively correlated to:

- Veteranity, i.e., the previous experience of the user in writing reviews.
- Lexical Diversity, i.e., the amount of unique words in the review.

These results are confirmatory towards the research of Schoenmuller et al. and are promising for the development of methods and tools for the research in the framework of social polarisation. They could be further developed into a causal model over a wider empirical corpus.

Other insights are:

- Adopting languages as proxies for cultures, it seems that cultural and maybe religious ideas have an easily observable effect when RB is driven by ideological reasons.
- Reverse ‘Review Bomb’ is a phenomenon still largely unchecked in both scientific literature and journalism. In particular, it is clear in the study that the negative Review Bomb over TLOU2 backfired after Phase 2, resulting...
into a positive (or reverse) ‘Review Bomb’. Is very hard in this study to differentiate positive ‘bombers’ from regulars who opposed negative ‘bombers’, unless through their veteranity.

- The survival function of veteranity among the corpus is a power law. Further research may demonstrate if other evaluands have different forms of decay in the veteranity of their reviewers, and what are the determinants of this shape. The presence of ‘bombers’ who only reviewed TLOU2 is implied in the large prevalence of G1 (78% of English Corpus).

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