A network-based matching design for text mining of hyper-polarised online reviews

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Abstract
Online reviews provide users with the opportunity to rate various types of items such as movies, music, and video games using a combination of numeric scores and textual comments. The study proposes a novel method that combines network modeling with statistical matching to estimate the unbiased association between words and hyper-polarized items in online reviews. The application of this method to a sample of 40,665 items from the website Metacritic detects 218 hyper-polarized items; these are matched with an equal number of items using 8 covariates of item quality and network centrality. Application of the method reveals an unbiased association between hyper-polarization and semantics indicating reactive social action in online reviews, especially related to controversial political issues in the USA.

Keywords
review bomb, polarisation, bipartite networks centrality, statistical matching, text mining

Introduction

This manuscript concerns text mining in online reviews. In online reviews, users rate items by a numeric score and a textual comment. Items can be consumer goods, services, etc (Stöckli and Khobzi 2021; Watson and Wu 2022; Sharkey et al. 2023). Some items can be clustered around their standing out as statistical outliers. Extremely Bi-Polar Items (EBI) are an example of these statistically peculiar items: they exhibit anomalous inflation in the frequency of maximum and minimum scores of the multipoint rating scale.

Observing the empirical frequency of meaningful words in reviews of the items within the cluster can help to understand why these items are so peculiar. But the direct comparison between in-cluster vs. out-cluster is problematic because the inference of the unbiased association would require an adjustment for the exposure of the two groups and of the word frequencies to the effect of covariates. This study claims that due to the intricate nature of explicitly specifying the causal structure of the relationship between textual corpora and statistical distributions, the optimal estimator for an unbiased association score is obtained through a statistical matching technique between elements within and outside of the cluster (Ho et al. 2007; Imai et al. 2008; Seawright and Gerring 2008; Aral et al. 2009; Stuart 2010; Morgan and Winship 2014; Steiner et al. 2015; Dong et al. 2021). The proposed methods has minor advantages, for example, it reduces the computational burden of the procedures of text mining, by optimising the number of comparisons.

In order to achieve this result, reviews are modeled as a network of users and items, and network-based statistics are attributed to the items as covariates of the matching algorithm (Aral et al. 2009; Charkhabi 2014; Dewan et al. 2017).

The study is roughly divided into four main sections, plus a final comment on the generalisation of the proposed observational design. The first is an overview of the theoretical and methodological issues involved in statistical modelling of online reviews. Here is also organically

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presented the issue of the operative definition of polarisation of ratings score as inherently relevant to the general statistical theory of online ratings.

The second section details the design as the combination of three operations: definition of the clustering, specification of the matching procedure, and proper processes of text mining.

The third section is an application of the methods. $1,552,750$ public reviews are collected by $40,665$ items of theplatform Metacritic (Kasper et al. 2019; Santos et al. 2019). 218 EBI are detected and matched. Some topics are found as particularly related to EBI: politics and morality, commercial brands, and sexuality. However, the most salient semantic concept is the mention of review bomb, a phenomenon documented in Cantone et al. (2023), in which a large number of users start a boycott campaign against an item. Limitations of the validity of these results are presented in the fourth section.

Why is it so hard to specify a network model of online reviews?

Classical models of online reviews

Let a publicly available catalog of items in a website of online review be the vector $\mathbf{i}$ and let the vector of user accounts of the platform be $\mathbf{u}$. Let a review be a vector j of information of different natures (text, score, time, etc.). j concerns the interaction between a sender node u, that is the reviewer or the user of the platform, and the receiver node i, that is the item in the catalog of the platform. The interaction is symbolised as $i \rightarrow u$, so $j_{u,i}$ counts as a link in a bipartite network. The number of links sent by a user is the sender degree k_u, and the number of links received by an item is the receiver degree k_i (Latapy et al. 2008; Graham and Paula 2019).

A relevant covariate (or, attribute) across j is the rating score y, a number that the user assigns to the item within an interval scale $(0 : m)$. 0 is the minimum value and m is the maximum. y is assumed to be the numeric equivalent to the expression of a feedback sentiment of the user towards the item, hence a positive measure of the sentiment. y can be observed for some combinations (u, i) but almost never for all possible combinations of u and i.

The following is an example of model with a very simple functional form for the determination of the rating score:

$$
\begin{aligned}
y &= \mathcal{B}(n; p) \\
n &= m \\
p &= \theta \cdot \alpha_i + (1 - \theta) \cdot \beta_u
\end{aligned}
\tag{1}
$$

α_i is a fixed latent attribute of the item that can be easily assumed to be its 'quality'; β_u is a fixed value for the user u, which is the general tendency of the user to rate items positively; θ is the global tendency to let the quality of the item prevail however the user's inclination for the determination of the rating score and $\mathcal{B}$ is the symbol for the Binomial distribution of n binary draws with p probability.

Assumptions of Eq. 1 are that α_i exists as latent propriety of the item and that β_u is stochastically stable over time: users do not rate more or less positively the more they review items. Minor assumptions of the model regard the modellisation of sources of errors (e.g. the moodiness of the user at the time of the review) as a noise ϵ with an ignorable effect on the average case.

The message conveyed in presenting Eq. 1 is that even a very simple Binomial model with strong assumptions (e.g. on the stability over time of β_u) would still require the estimation of three parameters. In practice, it is observed that the sample mean of the received rates $\bar{y}_i$ is adopted as an estimator for α_i (de Langhe et al. 2016; Santos et al. 2019; Janosov et al. 2020), instead. Compared to Eq. 1, the implicit assumption behind this practice is that β_u is just another source of unbiased error of $\bar{y}_i$, equivalently to set $\theta = 0$ and $\bar{\epsilon}_\nu = 0$.

Such a set of assumptions is not baseless: according to Hu et al. (2009) these assumptions are satisfied in experimental studies on rating behaviours (e.g. focus groups). However, they do not hold for online platforms, which are typically characterised by a bi-modal, concave, shape (J-shape). Hu et al. (2017) explain the J-shape as determined by:

1. Cognitive availability. The probability to receive reviews is higher for well-known, famous, items.
2. Sentimental commitment. If u knows i, he will provide feedback on i more likely if he feels a strong sentiment towards it. This bias also regards k_i because items with extremely high or low α_i should reach a higher degree k_i.

According to Hu et al. (2009) k_i and $\mathbb{E}(y_i)$ should be correlated because availability implies also a favorable opinion of the item. However, in the large dataset of ratings observed in Electronic Supplement of Janosov et al. (2020) is reported no Kendall correlation between k_i and $bary_i$.

This model is disputed by Brandes et al. (2022). According to their alternative, the polarity of online reviews is also explained by users with moderate inclinations towards rating products being more likely to leave the pool of active reviewers.

Inflated polarity in online reviews

Going beyond the characterisation of Hu et al. (2009) and of Brandes et al. (2022), there are other reasons to observe a J-shape in $\mathbf{y}_i$. It is often unclear if for the user the feedback sentiment regards a personal experience of the item or a more general opinion. Indeed, the latter can be socially induced even in the absence of a direct experience. For example, a user can think: "I dislike this movie because it offends my religion, and I do not need to watch it, because someone else told me enough details on it."

If not differently specified, $j_{u \to i}$ does not imply necessarily that u purchased or actually used i or that u truly holds a sentiment towards i, since he can just follow the request of a third party (Anderson and Simester 2014; Lee et al. 2021), or that u is not actually another user under disguise (a sock-puppet), or is an artificial agent, a *bot* (Ferrara et al. 2016; Kumar et al. 2017). These cases are nuances of deception and disinformation involved in online reviews. According to Wu et al. (2020), fake reviews could range from 10% to 30%. Fake reviews are associated with a high frequency of $y_i = m$ (Anderson and Simester 2014; Mayzlin et al. 2014). This phenomenon is explained by the practice of brand of "astroturfing": artificially inflate ratings (Ratkiewicz et al. 2011; Petrescu et al. 2022).

In other cases, disgruntled users organise themselves to push lower scores, with the aim of boycotting an item. This behaviour is commonly called "review bombing" (Cantone et al. 2023). The documented existence of astroturfing and review bombing implies that those who perform such acts believe in being influential over others with their actions. However, consequences can be chaotic and misaligned with the original intents: Cantone et al. (2023) show that after a review bomb it is possible to observe a spontaneous campaign of support for a sabotaged item. Hardly a simple parametric model as Eq. 1 is sufficient to infer associations with the collective behaviour of users, because different populations (or, classes) of users follow differents behavioural models.

This inconvenient claim holds for association (e.g. of specific semantic patterns) with $\bar{y}_i$ and, a fortiori, for associations with $\mathbb{U}(y_i)$, where $\mathbb{U}$ stands for a generic operative definition of polarity in the y scores. Despite this, understanding what drives the inflation of the bi-polarity in the y_i sample aside the classical theories is relevant because it is a key feature of statistical behaviours in online reviews.

The hypothesis is that Extremely Bi-Polar Items (EBI) have peculiar latent characteristics that make them targets of polarisation, e.g. these could be items dealing with naturally controversial topics. These latent characteristics can be semantically mirrored in the words of the reviews of EBI, hence the relevance of unbiased estimation of the association of keywords to EBI.

However, in an observational study just comparing frequencies of words mentioned or not in EBI would mostly reflect biases in the sample. For example, Cantone et al. (2023) suggest that EBI are associated with high k_u, which is also a simple measure of centrality in the Network Analysis. It can be interpreted as a cue that EBIs are regarded as more relevant by both regular users and agents of information. This is coherent with the aforementioned theory of cognitive availability: determinants of inflated polarity would make the item more famous (e.g. through external action of dedicated media), enabling a mechanism of preferential attachment towards these items, which could also result in a form of confounding bias for estimation of the association between words and clusters.

Network-based matching design

Without an explicit strategy to adjust for covariates, it is not possible to assess if the observed associated words mirror a difference in intrinsic features of inflated polarity instead of a difference in relevancy, centrality, or other structural confounders of the textual association. To overcome this issue, it proposed a design made by the following elements:

- A measure $\mathbb{U}$ for polarity, with a threshold $\vartheta(\mathbb{U})$ must be identified. Items with a $\mathbb{U}$ above the threshold are the EBI.
- Z covariates must be identified among the attributes of the items. Each EBI is matched to its non-EBI nearest neighbor, minimising the Z-dimensional Mahalabonibis distance.

- In this context, text mining involves fundamentally all the procedures necessary to link words to EBI through a numeric score of association, let it be η.

How to measure polarity?

Intuitively, polarity in a multipoint scale is defined as a inflation of extreme scores (Fisher et al. 2018; Schoenmueller et al. 2020). Schoenmueller et al. (2020) define $\mathbb{U}$ with a simple nonparametric index, which can be generalised as follows:

$$\mathbb{U}_0 = f(\min(y)) + f(\max(y)) \tag{2}$$

This indicator is misleading for cases of only inflated minimum or only inflated maximum, and also for monotonic distributions of y. A robust alternative is the following:

$$\mathbb{U}_{np}(y) = \min\Big(f(\min(y)) + f(\max(y))\Big) \cdot 2 \tag{3}$$

which is more conservative and easier to interpret: for example, differently from the index of Schoenmueller et al. (2020) it has a univocal interpretation of $\mathbb{U}_{np}(y) = 1$, since it happens only for $f(\max(y)) = f(\min(y)) = .5$.

From the last consideration a semi-parametric alternative is proposed, which is the ratio between the sample variance of y_i over its maximum, considering $n(y_i) = k_i$):

$$\mathbb{U}_{sp}(y) = \frac{\widehat{Var}(y)}{\arg\max(\widehat{Var}(y))} \tag{4}$$

Eq. 4 satisfies $f(\max(y)) = f(\min(y)) = .5 \to \mathbb{U}_{sp}(y) = 1$. In Appendix A is demonstrated that since $y \in (0:m)$, then

$$\lim_{k\to\infty} \arg\max\Big(\widehat{Var}(y)\Big) \tag{5}$$

converges to finite values that depend only on m. It holds the approximation:

$$\mathbb{U}_{sp}(y) \simeq \frac{\widehat{Var}(y) \cdot 4}{m^2} \tag{6}$$

Finally, since $\mathbb{U}_{np}(y)$ and $\mathbb{U}_{sp}(y)$ are both in the unit interval scale and they share the same conditions for minima and maxima, they can be composite through their harmonic mean:

$$\hat{\mathbb{U}}(y) = \frac{2}{(\mathbb{U}_{np}(y))^{-1} + (\mathbb{U}_{sp}(y))^{-1}} \tag{7}$$

Matching algorithm and covariates

The matching algorithm pairs each element in the cluster with the most similar element out of the cluster through a Nearest Neighborhood algorithm that aims at minimization of the distance between the item and its 'potential twin' out of the cluster. The distance is measured over a $\mathbf{Z}$ set of observable covariates of the items.

Among these covariates, one must make a distinction between covariates which are direct attributes of the item from those which are indirectly computed from the network structure, hence are structural covariates. While the firsts are usually accessed in the phase of data collection, structural requires a model of computation.

The following is a list of structural attributes from a network model of online reviews:

Measures of quality $\bar{y}_i$ the sample mean of public scores from collected public reviews $j_{u\to i}$. As aforementioned, it is usually employed as an estimator of α_i (see Eq. 1).

$\mathbb{E}(y_i \mid u)$, or just $e(y_i)$ is the prior for $\bar{y}_i$. It assumes knowing (only) the vectors of scores $\mathbf{y}_u$ submitted before $y_{u\to i}$, for all the u who reviewed i. This expectation is estimated through the following operations:

1. u with at least one $j'_{u\to i'}$ review before $j_{u\to i}$ are listed.
2. For each of them is computed

$$e(y_u) \mid i = \bar{y}_u \mid j'_{u\to i'} \tag{8}$$

   , which is the average of their scores before i.
3. Since each u weighs equally in determination of $\bar{y}_i$, the estimator of the expected $e(y_i)$ is just the average of the averages:

$$\mathbb{E}(y_i \mid u) \sim \bar{e}(y_u) \mid i = e(y_i) \tag{9}$$

Measures of centrality Network centrality of the node is a concept associated with the relevance of an item conditional to the cognitive availability (fame) of it among the users.

k_i is the *direct* measure of the Degree centrality of the item. In conventional applications, Degree centrality is sometimes, but not always, interpreted as measures of fame. The median $Med(k_u)$ of the users who reviewed i is the *indirect* measure of the Degree centrality of the item. $f_{k=1}$ is the frequency of $k_u = 1$ for $u \to i$. It is a relevant non-parametric statistic because it is a spurious measure (it is correlated to) of the share of agents of disinformation targeting the item, given that an agent of disinformation can always sign up with a new disguise (sock puppet, botnets) and push more scores and reviews (Kumar et al. 2017; Cantone et al. 2023).

Finally, there are measures expressly designed to measure centrality in bipartite networks. The reason to adopt ad-hoc measures is that conventional interpretations of centrality do not hold entirely for the phenomenologies modeled after bipartite networks. For example, it is controversial to assert that a sender, being an agent, has proprieties isomorphic to topological proprieties of a place with no *agency*.

Often methods for measuring the centrality of only a class of nodes (senders or receivers) involve redefining the bipartite network as a "one-mode projection" of that class, that is the network where one of the two original classes (senders or receivers) is kept as nodes, and the other is redefined as links. It is debated if one-mode projections bring a relevant loss of structural information through the suppression of the nodes (Lehmann et al. 2008).

In this study, the `Birank` score (He et al. 2017; Yang et al. 2020) is chosen as another measure of centrality. The Birank's algorithm has been developed expressly to avoid the one-mode projection and it has been evaluated as the best-performing algorithm for the centrality of nodes in bipartite networks (Yang et al. 2022). The interpretation of `Birank` scores for items is analogue to the PageRank algorithm. Higher Birank's scores are associated with items that receive many reviews from users who review many items with high k_i.

Text Mining

Text mining involves procedures for converting textual comments into statistical objects, and for associating these objects to EBI. A classical technique called 'bag-of-words' is proposed: reviews are tokenised and stopwords are filtered out (Silge and Robinson 2017; Gentzkow et al. 2019).

The nested structure of the corpus has four levels: groups, items, reviews, and tokens. The two groups (EBI and matched) have the same number of item. Each item is equivalent to a randomly-sized sample of reviews, and each review is a randomly-sized vector of tokens.

To account for this structure in the definition of the unbiased association score $\eta_{\mathbb{U}}(token)$ between a word and the EBI cluster, the following metric is adopted: the number of reviews in which the word appears at least once is counted for each item. One is added to this count, and then it is divided by $k_i + 1$. The resulting number is always positive and is transformed through the *logit* function*. The logit value assigned between the token and EBI is then subtracted from the logit value assigned to that same token and the matched (not EBI) item. The sum of these differences is divided by the number of EBI (the cluster size) and multiplied *per* 100 to improve readability of results. The estimator of η is formalised as follow:

$$
\begin{aligned}
c^{(1)}(token) &= logit(\frac{(\#j_i + 1) \mid token \in j_i}{k_i + i}), i \in EBI \\
c^{(0)}(token) &= logit(\frac{(\#j_i + 1) \mid token \in j_i}{k_i + i}), i \notin EBI \\
\hat{\eta}(token) &= \frac{c^{(1)} - c^{(0)}}{\#EBIs} \cdot 100
\end{aligned} \tag{10}
$$

In order to score a high η, a word must appear frequently in many EBI and few or no non-EBI, but it also must be frequent in many reviews of the same EBI. Also, the η estimator, being the average difference (and not a difference of averages), fully accounts for the matched structure of the items.

*$logit(x) = \ln \frac{x}{1-x}$

Application

Data

A sample of $1,552,750$ public reviews (j) has been collected across $40,665$ items from the catalogs of the platform Metacritic. Users can review an item privately; these reviews cannot be collected, instead. In this platform, the multipoint scale is $(0:10)$ and items are classified as movies ($n = 10,617$), music albums ($n = 8,431$), serial shows ($n = 3,318$ seasons) and video games ($n = 18,299$). j links u to i, and has a textual comment, a score, and the day of submission as attributes. The oldest sampled review has been submitted on January 2001 while the last one on November 2021.

The average score in the sample is $bary$ = 7.14. The median number of reviews *per* item is $Med(k_i) = 7$, with 22 being the 75^{th} and 65 the 95^{th} percentile. Confirming the findings of Janosov et al. (2020), the Kendall correlation between k_i and $bary_i$ is trivial (-0.02).

$635,781$ unique users are detected. Summed to $40,665$ items they constitute a bipartite network of 676.446 nodes. Of these users, $453,359$ ($.713$ of total) submitted only a public review, $82,909$ ($.13$) submitted two public reviews, 22.691 ($.05$) submitted three, and $17,250$ four. Only 8% of users submitted more than four public reviews on Metacritic.

The Theory of Attrition (Brandes et al. 2022) does not fit evidence from the Metacritic dataset, while the assumption of Eq. 1 on the stochastic stability of β is not rejected, since users with a large number of past reviews use less extreme scores but overall the rating behaviour seems time-independent (see Fig. 1).

Collected items are directly associated with attributes provided by Metacritic. These are:

- The UserScore or `US`, is a number that represents an estimate of the quality of the item, based on both public and private scores. This information is displayed through browsing the website Metacritic.
- The MetaScore or `MS` is another score assigned by Metacritic to items. It is a summary score of the judgment of expert journalists only. MetaScore represents the opinion of the experts.
- The `year` of publication of the item.

In the sample, the average bias of public scores is trivial: -0.06. For comparison, the mean difference between the users and the experts

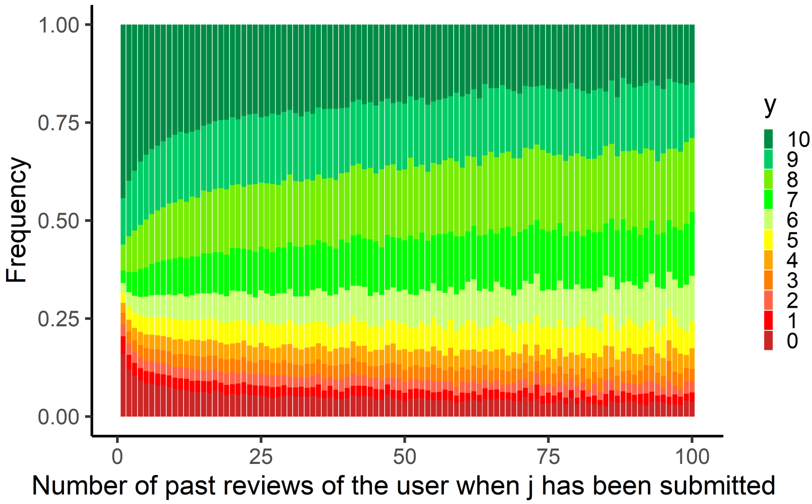

Figure 1. Less extreme scores are observed when users submit more public reviews on Metacritic.
On the vertical axis is represented the relative frequency of the scores. Interpreting these frequencies as probabilities, extreme values are much more likely for users for the first reviews of users. Scores are less extreme after users already reviewed some items in the past. This should be paired with the frequency of the number of reviews, that for $\sim 41\%$ is concentrated in the first bar of the plot (ku = 1) alone. It is plausible that these frequencies for low k_u are just biased due to the high number of users submitting only a review. This statistical behaviour is coherent with the hypothesis that a part of such users with k_u = 1 are agents of disinformation (astroturfers, saboteurs, etc.).

(MetaScore) is five times larger in absolute values: 0.3, which is coherent with previous findings (Santos et al. 2019). Given the negligible bias, public scores are assumed as representative of the whole population of public and private scores.

Criteria of exclusion from the sample In the analysis, 90% of items in the sample received less than 66 public reviews. They are undersampled for robust text mining and Possibly they lack relevance too, so they will be excluded from the analysis. 42 items are excluded because Metacritic did not assign a MetaScore to them. The video game “The Last of Us Part 2” is excluded from this selection because it is an outlier: it is the item with the largest $k = 78,219$ (Cantone et al. 2023), by far much more than any other.

Classification of EBI

In Table 1, indicators polarity are always negatively correlated with indicators of quality. This correlation is likely mediated by k_i: the considered selection of the $3,978$ items in the top 10% of k_i do not show this correlation anymore. The full range of correlation within the covariates is in Appendix B, tables etc etc

Table 1. Kendall correlations of measures of polarity with other indicators

	Total Sample		$k_i > 65$	
	$\mathbb{U}_{np}$	$\mathbb{U}_{sp}$	$\mathbb{U}_{np}$	$\mathbb{U}_{sp}$
`US`	-0.14	-0.29	-0.44	-0.49
`MS`	-0.02	-0.14	-0.16	-0.19
$\bar{y}_i$	-0.26	-0.48	-0.49	-0.57
$e(y_i)$	-0.12	-0.17	-0.25	-0.28
k_i	0.38	0.19	0.07	0.05
$Med\ k_u$	-0.18	-0.13	-0.24	-0.24
$f_{k=1}$	0.16	0.14	0.24	0.27
`Birank`	0.37	0.17	0.03	0.03
$\mathbb{U}_{np}$	1.00	0.52	1.00	0.76
$\mathbb{U}_{sp}$	0.52	1.00	0.76	1.00

Among these $3,978$ candidates with $k > 65$ public reviews, 218 EBI are identified as the items with a $\hat{\mathbb{U}}(y_i)$ over the 95^{th} percentile ($\vartheta(\mathbb{U}) = .42$), see Figure 2. Of these 218 EBI, 26 are movies, 37 are music albums, 19 are seasons of serial shows, and 136 are video games.

Matching

The 218 EBI are paired with other 218 item not classified as EBI. The matching algorithm follows the following rules:

- EBI can only be matched with items of the same class (movies with movies, etc.).
- Nearest Neighbour Search (NNS) is performed among the eligible items, aimed at minising the multivariate Mahalanobis distances towards the EBI for 9 control covariates: `US`, `MS`, $\bar{y}_i$, $e(y_i)$, k_i, $Med(k_u)$, $f_{k=1}$, `Birank`, and the `year` of publication

The NNS algorithm converged towards satisfying results, excepted for $Med\ k_u$ which is persistently lower in EBI (Table 2). In the 218 matched

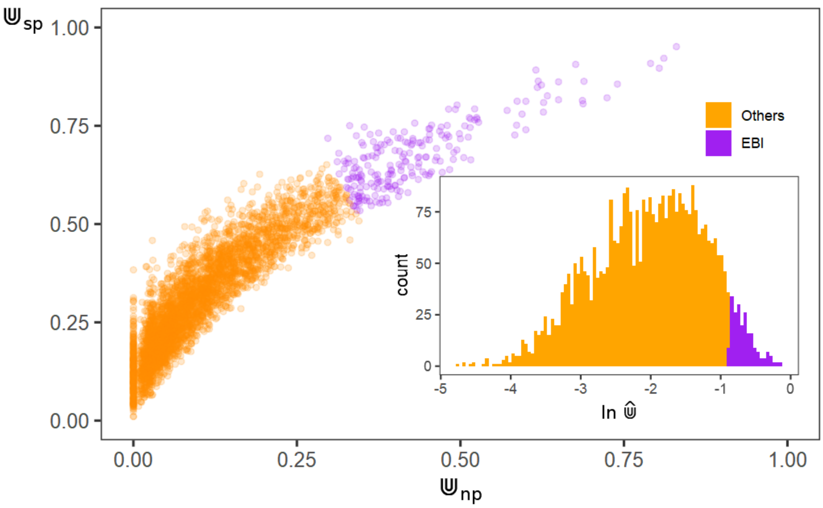

Figure 2. Densities of polarity scores across items with $k_i > 100$ in the two clusters. Most of the probability mass of $\hat{\mathbb{U}}(y_i)$ is concentrated between $\exp(-1) = .36$ and $\exp(-3) = .05$.

items polarity is higher than in the pool of $3,759$ RI candidates, but they are still significantly lower than in EBI, which are characterised as extreme cases of polarity.

Table 2. Evaluation of the matching results

		All	EBI	Matched
$\sum$	n	3,759	218	218
$\sum$	k_i	944,769	93,162	85,962
$avg.$	$\mathbb{U}_{np}(y_i)$	0.10	0.43	0.20
$avg.$	$\mathbb{U}_{sp}(y_i)$	0.30	0.67	0.47
$avg.$	$\hat{\mathbb{U}}(y_i)$	0.14	0.52	0.27
$avg.$	US.	7.35	5.45	5.79
$avg.$	$\bar{y}$	7.22	5.23	5.59
$avg.$	MS	7.35	5.45	5.79
$avg.$	$e(y_i)$	7.18	6.56	6.66
$avg.$	$Med(k_u)$	13.97	3.63	4.75
$avg.$	$f_{k=1}$	0.21	0.34	0.31
$-\ln$	Birank	10.73	10.70	10.70
Med	year	2013	2017	2016

Findings

Only $78,062$ EBI reviews and $74,782$ matched reviews in English are considered[†]. In the aggregate *corpus* of $152,844$ reviews, the tokens consisting of less of three symbols have been filtered out, and η has been estimated for $100,952$ tokens.

Just looking at the top scoring 220 token semantic patterns emerge (Table 3). The second token most associated with EBI is "bomb", which is linked to the aforementioned concept of review bombing, as confirmed by the presence of "bomber" in the first column of Table 3. It is a signal that users commenting on highly polar items are aware of participating in a controversial discussion and are often semantically reactive in their reviews, mentioning others' behaviours. Reactive social behaviour emerges from the concepts related to main tokens. All tokens with the highest $\hat{\eta}$ point to concerns towards the veracity of content in EBI: "haters", "propaganda", "troll", "fake". These words signal concern against correct information being altered ("misinformation, 4^{th} column, $\hat{\eta} = 4.61$") by someone else (a 'bomber', a 'hater, a 'troll', a 'fake'); in this sense, the user reviews the EBI having the past actions of someone else in mind (Cantone et al. 2023). The presence of tokens for social media"twitter" and "reddit" and of "journalist" is pairwise noteworthy.

Other topics can be identified:

- USA Politics and religions: tokens such as "propaganda", "liberal", "leftist", "conservative", "republican" are part of the USA political jargon. Other words are political in nature, such as "election", "vote", "agenda", and "politic". "hillary" "clinton" is directly mentioned among the tokens of Table 3. "russian" could be related given the high η, alongside "west". Other words that are less political but are allusive of a semantic of religious morality: "christian", "saint", "abortion", "jesus", "atheist", "muslim", "christ"; but also "abortion", which is actually a relevant topic of debate in current USA politics.
- Brands: "gta", "sony", "cyberpunk", "batman", "bieber", "rockstar", "nicki", "geforce", "blizzard", "balan", "metacritic", "hbo", "wii" are tokens for brands.

[†] Identified with the *R* package `cld3`, Google Compact Language Detector.

Table 3. Top 220 token associated to EBI

Token	$\hat{\eta}$	Token	$\hat{\eta}$	Token	$\hat{\eta}$	Token	$\hat{\eta}$	Token	$\hat{\eta}$
haters	17.29	law	7.31	arkham	5.77	dmc	4.88	chord	4.32
bomb	15.37	agenda	7.30	captain	5.75	who've	4.87	chick	4.31
propaganda	15.33	pve	7.13	innocent	5.73	charlotte	4.87	gow	4.30
troll	14.61	pretend	7.00	accessory	5.72	april	4.85	atheist	4.29
fake	13.15	goty	6.99	laugh	5.71	outrage	4.84	poser	4.29
child	12.78	loser	6.97	lil	5.67	unfair	4.83	airport	4.29
ban	12.73	tasteless	6.96	unoriginal	5.63	entitle	4.80	rap	4.27
theory	12.38	support	6.92	pathetic	5.62	punk	4.79	boob	4.26
house	11.64	keanu	6.92	footage	5.52	study	4.76	ariana	4.23
cute	11.06	whine	6.90	journalist	5.52	whore	4.76	language	4.22
sex	10.70	argument	6.72	anti	5.50	idiot	4.75	muslim	4.21
overpriced	10.69	leftist	6.67	baby	5.50	debate	4.75	ward	4.21
gta	10.22	debut	6.62	sane	5.43	jesus	4.74	clinton	4.19
activity	10.16	twitter	6.62	museum	5.41	dinosaur	4.72	nazis	4.19
looter	10.16	vote	6.56	streamer	5.39	motorsport	4.72	orc	4.19
liberal	10.15	riot	6.51	conservative	5.39	freely	4.68	anthem	4.17
fanboys	10.10	sexual	6.51	republican	5.37	butthurt	4.67	politic	4.17
disgust	9.95	justin	6.51	election	5.33	abortion	4.64	gran	4.17
west	9.87	trash	6.48	racism	5.33	misinformation	4.61	mario	4.16
article	9.69	premium	6.46	platformer	5.33	racist	4.58	promote	4.16
documentary	9.65	botw	6.38	platforming	5.29	nay	4.57	submit	4.16
zero	9.64	flop	6.35	artstyle	5.26	inform	4.56	portuguese	4.16
sony	9.63	cat	6.32	skew	5.26	provoke	4.55	cornell	4.14
girl	9.45	educate	6.30	bill	5.24	driver	4.54	funny	4.14
russian	9.26	democratic	6.29	service	5.24	toxicity	4.53	burger	4.13
terrorist	9.24	lol	6.25	sweetener	5.22	childish	4.51	deny	4.13
grindy	9.16	exp	6.24	ignorant	5.16	democrat	4.50	russia	4.12
bomber	9.12	beg	6.22	truth	5.15	wannabe	4.50	voter	4.12
island	8.55	reeve	6.21	minaj	5.15	dante	4.48	chopper	4.11
christian	8.49	offend	6.16	ashlee	5.15	breathtaking	4.48	homophobic	4.10
cyberpunk	8.44	coaster	6.12	mmr	5.15	theft	4.48	traffic	4.10
saint	8.27	lie	6.08	mobas	5.14	aircraft	4.47	resin	4.09
parent	8.21	moron	6.07	pedestrian	5.09	combo	4.45	lmao	4.08
forza	8.05	hillary	5.94	hardware	5.07	kat	4.44	warner	4.08
medium	7.93	expose	5.91	cry	5.05	balan	4.43	spec	4.08
hat	7.92	moore	5.91	singer	5.05	animal	4.43	shave	4.05
controversy	7.90	nickelback	5.90	gay	5.03	company	4.42	hbo	4.04
ticket	7.84	data	5.89	president	5.01	metacritic	4.41	wii	4.02
hunt	7.71	predatory	5.84	greed	4.97	cooperate	4.40	christ	4.01
batman	7.70	penis	5.83	sensitive	4.95	woman	4.39	billie	4.01
immature	7.63	offensive	5.81	reaper	4.91	shower	4.38	didn't	4.00
bieber	7.59	geforce	5.78	hate	4.88	bias	4.37	gaiden	4.00
rockstar	7.57	adult	5.77	blizzard	4.88	porn	4.35	reddit	4.00
nicki	7.34	endgame	5.77	someday	4.88	turismo	4.34	distort	4.00

- Sexuality: a minor but robust topic, it connects words related to sexual activities or to sexual slurs, examples are “sex”, “penis”, “adult”, “gay”, “whore”, “porn”, “homophobic”, “boob”. In this context, it is peculiar that all of “girl”, “woman” and “chick” are in the top 220, but not “boy” or “man”.

Limitations

This study presents a method and application, but it has three notable limitations that should be addressed. Firstly, the method's ability to causally infer from η is uncertain. While statistical matching methods like NNS algorithm reflect experimental control procedures, the quality of results depends on the availability of key covariates. Although high-scoring tokens suggest significant semantic differences between EBI and non-EBI, η alone is not enough to make a causal claim about the relationship between these topics and EBI's phenomenology. This is because the causal direction of the relationship is not uniquely identifiable since scores and reviews are submitted concurrently. To address this, further learning sub-procedures could be implemented for the validation of tokens' along the time-span of the item's review history (Egami et al. 2022).

The second limitation pertains to the external validity of the application's findings, specifically the extent to which the semantics associated with EBI can be generalized to online platforms of user reviews other than Metacritic. The user demographics on Metacritic primarily consist of young males residing in the USA with interests in science fiction and video games. As a result, the emerging topics in this study may not necessarily hold true for EBI across different cultures and languages, even if the variation in terminological expression is taken into account (e.g. *izquierda* instead of *liberal*). However, it is hypothesized that some of the emerging topics in this study could still hold general validity for EBI, but this must be further investigated in future studies.

The third limit concerns some irreducible degree of freedom of the method, that could condition the validity of the findings in the application. These are listed in Table 4 and shortly commented.

Table 4. Elements for a sensitivity analysis

Issue	Alternative
How to measure polarisation?	Alternative measures.
$Med(k_i)$ in the sample is very low	Consider a lower filter for k_i
Extreme polarity is not naturally clustered.	A different threshold.
Matching	Alternative distances
Topics are not automatically inferred	Pre-trained topic modelling

On the measurement of polarity

The application developed an operative definition of polarity which emerged from literature Schoenmueller et al. (2020). This definition is slightly different from the parametric characterisation of polarisation as bi-modality prevalent in Psychometrics (Knapp 2007; Pfister et al. 2013; Tang et al. 2022). As a parametric method, statisticians derive a parameter of overdispersion for a mixture model of the score (Iannario 2014), which in Piccolo and Simone (2019) is conceptually equated as a measure of the statistical entropy in the decision making. Econometrics has another different parametric approach that does not assume the duality of polarity and allows multi-polarity (Esteban and Ray 1994; Duclos et al. 2004; Deutsch et al. 2013).

Filtering low-reviewed items and clustering EBI

Filtering out $\sim 37,000$ may seem like a huge loss of information, but it actually improves the reliability of η avoiding accounting for items that are technically EBI, but there is no real public involvement in them - so the phenomenology could be substantially different[‡]. The main issue with filtering is that k_i follows scale-free distribution: it does not grow up linearly and does not distribute around a central value, so even non-parametric indexes as the median are only relatively informative (Barabási 2009; Holme 2019).

More concerning is the determination of the exact boundaries of the EBI cluster. Fig. 2 shows that polarity follows a logarithmic bell curve and EBI are the right tail (95^{th} percentile). But not all EBI are equally bi-polar since 16 of them are much more bi-polar than others. Inference could have been restricted to only those 16, but a larger sample helps for an accurate assessment.

Alternative matching

Compared to more elaborated alternatives such as the Optimal Matching algorithm (Hansen and Klopfer 2006) or Coarse Exact Matching (Iacus et al. 2012) which preserve global optima of distances through matching multiple controls or pruning cases out of the sample, NNS is considered

[‡]For example, if an item received only 20 reviews from regular users, it is relatively easy to astroturf other 20 reviews to improve $\bar{y}_i$. $\mathbb{U}$ is relatively robust to these phenomena, but in general polarity is associated to centrality, see Table 1.

a "greedy" algorithm: and it does not condition a match on the expected effects of reducing the pool of available items for the subsequent EBI. In this application, greediness is not an issue because there is a large pool of $3,759$ items to pair with only 218 EBI, hence the effect of reducing the pool of candidates for each subsequent matching is negligible.

The Mahalanobis distance is preferred to the alternative Propensity Scores[§] becuase in literature Mahalanobis is considered a less biased approach for a low number of control covariates (Stuart 2010; King and Nielsen 2019).

Topic modelling

The application still requires a human interpreter of the adjusted association, who understands the hidden semantic patterns behind the findings of the text mining procedure. Table 3 shows 220 tokens, but the model estimated η for more than 100,000 tokens, of which more than 99% are definitely unrelated to the phenomenology of EBI. Such richness of results could still be processed automatically by large pre-trained models (Lee et al. 2020; Qiang et al. 2022).

Final Comment

This study concerns the general feasibility of a methodological design to control for the effects of covariates in the estimation of the association between the semantics implied in online reviews and numeric proprieties as the polarity of their scores. Results confirm and expand the validity of preliminary results in (Cantone et al. 2023), establishing an incontrovertible association of review bombing to hyper-polarisation of reviews in Metacritic, over alternative explanation as astroturfing.

This design suits analysis on data retrieved from platforms of online reviews, where all of these features recur; but it can be extended or slightly adjusted to account for similar applications. For example, just adjusting the strategy for identification of the covariates, this methodological design would clearly suit the semantic analysis of the content of nodes of direct networks, like citation networks, whereas nodes would be textual documents (Light et al. 2021).

[§]The $e(i)$ coefficient of the probability $\mathbf{E}(x = 1)$, $x = 1$ is the membership in the cluster. $e(i)$ is usually the prediction value of a binary regression model $x = bZ + \epsilon$.

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Appendix A: On maximum variance for bounded random variables

The formula for the maximum variance for the X_m random variable defined in $(0:m)$ is derived in Bertsekas and Tsitsiklis (2002) as follows.

Given a constant c and a X random variable, it holds:

$$\mathbb{E}((X-c)^2) = \mathbb{E}(X)^2 - 2\mathbb{E}(c \cdot X) + c^2 \tag{11}$$

hence:

$$\min \mathbb{E}((X-c)^2) = 2\mathbb{E}(cX) \leftrightarrow c = \mathrm{E}(X) \tag{12}$$

From 12 it follows:

$$Var(X) = \mathbb{E}(X - \mathbb{E}(X))^2 \leq \mathbb{E}(X-c)^2; \forall\, c \tag{13}$$

Letting $c = \frac{m}{2}$, from 11 and 13 it follows:

$$Var(X_m) = \mathbb{E}(X_m - \frac{m}{2})^2 = \mathbb{E}(X_m(X_m - m)) + \frac{m^2}{4} \leq \frac{m^2}{4} \tag{14}$$

because given that $x \in X_m$ is positive by definition of $0 \leq x \leq m$, then $x(x-m) \leq 0$. Hence it follows 14 that $\frac{m^2}{4} = \max Var(X_m)$.

Appendix B: Correlation Matrixes

Table 5. Kendall correlations on the whole sample ($n = 40,665$)

	US	MS	$\bar{y}$	$e(y_i)$	k_i	$Med\,k_u$	$f_{k=1}$	Birank
US	–	0.36	0.54	0.22	0.09	-0.06	0.03	0.11
MS	0.36	–	0.31	0.10	0.10	-0.07	0.00	0.10
$\bar{y}$	0.54	0.31	–	0.29	-0.02	-0.09	0.03	0.01
$e(y_i)$	0.22	0.10	0.29	–	-0.03	-0.10	0.03	0.00
k_i	0.09	0.10	-0.02	-0.03	–	-0.18	0.22	0.82
$Med\,k_u$	-0.06	-0.07	-0.09	-0.10	-0.18	–	-0.49	-0.27
$f_{k=1}$	0.03	0.00	0.03	0.03	0.22	-0.49	–	0.33
Birank	0.11	0.10	0.01	0.00	0.82	-0.27	0.33	–

Table 6. Kendall correlations when $k_i > 65$ ($n = 3,978$)

	US	MS	$\bar{y}$	$e(y_i)$	k_i	$Med\,k_u$	$f_{k=1}$	Birank
US	–	0.37	0.78	0.39	0.03	0.07	-0.10	0.07
MS	0.37	–	0.34	0.16	0.15	-0.04	-0.03	0.12
$\bar{y}$	0.78	0.34	–	0.43	0.02	0.02	-0.08	0.05
$e(y_i)$	0.39	0.16	0.43	–	-0.03	0.05	0.06	0.04
k_i	0.03	0.15	0.02	-0.03	–	-0.16	0.12	0.77
$Med\,k_u$	0.07	-0.04	0.02	0.05	-0.16	–	-0.68	-0.09
$f_{k=1}$	-0.10	-0.03	-0.08	0.06	0.12	-0.68	–	0.11
Birank	0.07	0.12	0.05	0.04	0.77	-0.09	0.11	–

These 8 indicators are separated by the latent dimensions that they aim to define: quality and centrality of the items. It is expected that indicators of the same latent concept are correlated, and indicators of different concepts are not. With minor exceptions, the latter hypothesis is verified. Establishing if indicators within the same group are measuring the same latent concept is less straightforward. Noteworthy is that direct centrality (k_i) and indirect centrality ($Med(k_u)$) being negatively correlated, while `Birank` index (third order centrality) is correlated to k_i. These correlations are likely a side effect of the prevalence users with $k_u = 1$.