Public Discourse in the Web Does Not Exhibit Group Polarization

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Abstract

We performed a massive study of the dynamics of group deliberation among several websites containing millions of opinions on topics ranging from books to media. Contrary to the common phenomenon of group polarization observed offline, we measured a strong tendency towards moderate views in the course of time. This phenomenon possibly operates through a self-selection bias whereby previous comments and ratings elicit contrarian views that soften the previous opinions.
No aspect of the massive participation in content creation that the web enables is more evident than in the countless number of opinions, news and product reviews that are constantly posted on the Internet. Since these opinions play such an important role in trust building and the creation of consensus about many issues and products, there have been a number of recent of studies focused on the design, evaluation and utilization of online opinion systems [5, 6, 10, 11] (for a survey, see [7]). Given the importance of group opinions to collective social processes such as group polarization and information cascades [2, 3, 4, 15] it is surprising that with the exception of one study [13], little research has been done on the dynamic aspects of online opinion formation. It remains unclear, for example, whether the opinions about books, movies or societal views fluctuate a long time before reaching a final consensus, or they undergo any systematic changes as time goes on. Thus the need to understand how online opinions are created and evolve in time in order to draw accurate conclusions from that data.

Within this context we studied the dynamics of online opinion expression by analyzing the temporal evolution of a very large set of user views, ranging from millions of online reviews of the best selling books at Amazon.com, to thousands of movie reviews at the Internet Movie Database IMDB.com. Surprisingly, our analysis revealed a trend that runs counter to the well known herding effect studied under information cascades, and in the smaller instance of group polarization. Online, a self selection mechanism is at play whereby previous comments and ratings elicit contrarian views that soften the previous opinions.

It is well known that in the case of group polarization, members of a discussion group tend to advocate more extreme positions and call for riskier courses of action than individuals who did not participate in any such discussion [11, 17]. However, on the massive scale that the web offers, we observed that later opinions in the course of time tend to show a large difference with previous ones, thus softening the overall discourse. This is a robust and quantitative observation for which we can only offer a tentative explanation in terms of the cost of expressing an opinion to the group at large.

In order to perform this study we first analyzed book ratings posted on Amazon.com. Our sample consisted of the book ratings of the top 4,000
best-selling titles of Amazon in each of the following 12 categories, as of July 1, 2007: arts & photography, biographies & memoirs, history, literature & fiction, mystery & thrillers, reference, religion & spirituality, sports, travel, nonfiction, science, and entertainment. For each of the 48,000 books, a series of user ratings was collected in time order, where each rating is an integer between 1 and 5. Among the 48,000 books, 16,454 books have no less than 20 ratings, and 11,920 have an average rating above 4.

We first checked the average rating of the 16,454 books as a function of the index of the rating ($n = 1, \ldots, 20$). As can be seen from Fig. 1(a), $E X_n$ decreases almost linearly with $n$, so there is a clear dynamical trend in the ratings, which corroborates the observation reported in [13]. Later users tend to write different reviews from those of earlier users. Like in the experimental setup of group polarization, an Amazon user observes the existing average rating of that book before she leaves her own (usually shown at the top of the book page, right under the title). However, as opposed to group polarization, the overall opinion on Amazon tends to decrease away from the extreme ones.

One point to be stressed is that these results do not necessarily imply that as time goes on the average opinion of the whole population changes, for the late reviewers might come from a different group than the earlier ones and need not be representative of the whole population. This is seen when plotting the average “helpful ratio” as a function of star rating in Fig. 2 for users of Amazon. As can be seen, the whole population finds high ratings in general more helpful than low ratings, implying that the majority of the population does not necessarily agree with the low ratings. This additional data suggests that rather than indicating a real opinion shift in the whole population, the observed dynamic trend is more of an expression bias.

On reflection, it is rather surprising that people contribute opinions and reviews of topics which have already been extensively covered by others. While posting views is easy to understand when it involves no effort, like clicking on a button of a website, it is more puzzling in situations where it is costly, such as composing a review. When a user of Amazon decides to review a book, she is required to write a short paragraph of review in addition to a simple star rating. The average word count of Amazon

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Figure 1: (a) The average rating of 16,454 books on Amazon.com with more than 20 reviews. $E X_n$ is the sample average rating of all the 16,454 $n^{\text{th}}$ ratings. As one can see from the figure, $E X_n$ decreases by 0.4 stars in 20 steps. We did not obtain enough data from low selling books to show the opposite trend.

opinion or rating diminishes with the number of published ones, why does anyone bother to incur the cost of contributing yet another review? From a rational choice theory point of view, if the utility to be gained does not outweigh the cost, people would refrain from expressing their views. And yet they do. This is reminiscent of the well analyzed voter’s paradox [9, 14, 16], where a rational calculation of their success probability at determining the outcome of an election would make people stay home rather than vote, and yet they show up at the polls with high turnout rates. In contrast to a political election, there is no concept of winning in online opinion systems. Rather, by contributing her own opinion to an existing opinion pool, a person affects the average or the distribution of opinions by a marginal amount that diminishes with the size of that pool.

One possible explanation for these results is that in cases like Amazon, people will derive more utility the more they can influence the overall rating, as in the voter’s paradox. To be precise, in cases where users’ opinions can

reviews is 181.5 words [12], so the cost of opinion expression is indeed high.
Figure 2: (a) The average helpful ratio of five different star ratings. (b) The average review length of five different star ratings in the number of characters. The data is calculated for 4,000 bestselling mystery books. By comparing the two figures it is clear that people find high ratings more helpful not just because they are longer. For instance, 5-star reviews are on average shorter than 4-star and 3-star reviews but are nevertheless more helpful.
be quantified and aggregated into an average value, the influence of an online opinion can be measured by how much its expression will change the average opinion. Suppose that \( n \) users have expressed their opinions, \( X_1, \ldots, X_n \), on a given topic at a website, with \( X_i \) denoting the quantified value of the \( i \)'th opinion. If the \((n+1)'\)th person expresses a new opinion \( X_{n+1} \), it will move the average rating to

\[
\bar{X}_{n+1} = \frac{n\bar{X}_n + X_{n+1}}{n + 1},
\]

and the absolute change in the average rating is given by

\[
|\bar{X}_{n+1} - \bar{X}_n| = \frac{|X_{n+1} - \bar{X}_n|}{n + 1}.
\]

Thus a person is more likely to express her opinion whenever \( |X_{n+1} - \bar{X}_n| \) is large — an opinion is likely to be expressed if it deviates by a significant amount from those already stated. Indeed, what is the point of leaving another 5-star review after one hundred people have already done so?\(^2\)

In order to test this hypothesis, we measured directly how much one’s rating deviates from the observed average rating. We plot the expected deviation \( Ed_n = E|X_n - \bar{X}_{n-1}| \) as a function of \( n \) in Fig. 3, where \( X_n \) is the rating left by the \( n \)'th user, and \( \bar{X}_{n-1} \) is the average rating the \( n \)'th user observes. As can be seen, \( Ed_n \) increases with \( n \). Since the expected deviation \( Ed_n \) of an i.i.d. sequence normally decreases with \( n \), this increasing trend is indeed significant. This again supports our conjecture that those users who disagree from the public opinion will be more willing to express themselves and thus soften the overall opinion of a given book.

Next we examined whether this dynamical trend is still prominent at the level of each individual book. We defined \( d = \bar{X}_{20} - \bar{X}_{10} \) as a measure of the change in a book’s rating over time. The histogram of 16,454 \( d \)'s is shown in Fig. 4. As can be seen, most of the changes are negative. A \( t \)-test of the alternative hypothesis “\( d < 0 \)” yields a \( p \)-value less than 0.0001, which further confirms the declining trend.

\(^2\)This point has also been made within the “brag-and-moan” model \([8, 11]\) which assumes that consumers only choose to write reviews when they are very satisfied with the products they purchased (brag), or very disgruntled (moan). Note however, that the brag-
Figure 3: The average deviation of Amazon ratings increases with the number of people.

Figure 4: Histogram of the change in average book ratings \((d = \bar{X}_{20} - \bar{X}_{10})\) on Amazon.com. Most of the changes are negative, testifying a declining trend in the average ratings.
While our hypothesis of a costly expression bias seems to explain the softening of opinions observed in Amazon, it would be more conclusive if one could conduct a test that directly compares people’s opinions expressed at different cost levels. In order to address this issue we conducted a study of IMDB.com (The Internet Movie Database). Unlike users of Amazon who are required to write a review when rating a book, users of IMDB are free to choose the effort level when reviewing a movie. Specifically, after observing the current average rating of a movie, a user can either submit a quick rating by clicking on a scale of 10 stars, or can make the extra effort involved in writing a comment between 10 and 1000 words.

Our study focused on two sets of movie titles. The first consists of the 50 most top-rated movies released after year 2000, which we call the “good movies”, and the second consists of the 50 most low-rated, which we call the “bad movies”. For each movie we know its average rating (taken among all ratings with or without a comment), as well as the value and date-stamp of its each commented rating, but we do not have any specific information about each uncommented rating.

The trend of the ratings associated with comments of the two sets of movies is shown in Fig. 5. Similar to Amazon, a softening of the expressed view is once again observed for both sets. Two histograms of \( d = \bar{X}_{10} - \bar{X}_5 \) for the good movies and the bad movies are shown in Fig. 6. A \( t \)-test of the alternative hypothesis \( d < 0 \) for the good movies yields a \( p \)-value 0.44. A \( t \)-test of \( d > 0 \) for the bad movies yields a \( p \)-value 0.018. While it is not too reliable to conclude that good movies tend to receive lower ratings over time, it is safer to conclude that bad movies accumulate higher ratings as time goes on.

We also examined the difference between the overall average rating (with or without a comment) and the average rating associated with a comment for each movie, and the result is shown in Fig. 7. It can be seen that those who decide to spend the time to write a comment tend to speak differently from the majority users, who simply leave a star rating without any justification. Fig. 7 is thus a direct verification of our hypothesis that high cost induces

and-moan model is static and thus predicts that \( \bar{X}_n \) is constant over time, in contradiction with the observed dynamical trends.
Figure 5: Average rating associated with a comment of the (a) good and (b) bad movies, as a function of the number of existing ratings. It can be seen that good movies tend to receive lower ratings as time goes on, and bad movies tend to receive higher ratings.

Figure 6: Histogram of $d = \bar{X}_{10} - \bar{X}_5$ for the good movies and bad movies.
Figure 7: Expression bias of commented ratings. Each point in this figure corresponds to one movie title. The horizontal coordinate represents the movie’s overall average rating ($\bar{r}$) taken over both commented and uncommented ratings. The vertical coordinate represents the movie’s average rating taken over only commented ratings ($\bar{r}_c$). Good and bad movies are represented by circles and crosses, respectively. Clearly, those users who spend the additional cost to write a comment tend to speak oppositely to the majority. A $t$-test of the alternative hypothesis that $\bar{r}_c < \bar{r}$ for good movies and a similar $t$-test of $\bar{r}_c > \bar{r}$ for bad movies both yield a $p$-value less than 0.001.

These results show that in the process of articulating and expressing their views online, people tend to follow a different pattern from that observed in information cascades or group polarization. What is observed is an anti polarization effect, whereby previous comments and ratings elicit contrarian views that soften the previous opinions. This is in contrast to the phenomenon of herding and opinion polarization observed in both group dynamics and online sites.\footnote{We point out that in a website like JYTE.com, where it takes only one click to agree or
In closing, besides their intrinsic novelty, these results throw a cautionary note on the interpretation of online public opinion. This is because a simple change in the order or frequency of given sets of views can change the ongoing expression in the community, and thus the perceived collective wisdom that new users will find when accessing that information.

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disagree with an arbitrary claim, we did see a strong group polarization [15]. It is possible that the latter is due to the fact that such a vote is costless compared to the opinions on Amazon and IMDB.
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