Effects of Social Influence in Peer Online Recommendation

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(Dated: October 27, 2014)

Abstract

Web site providers often use peer recommendation to help people find interesting content. A common method for leveraging opinions of others on these web sites is to display the number of prior recommendations as a social signal. How people react to these social influence signals, in combination with other effects, such as the quality of content and its presentation order, determines how many recommendations content receives. Using Amazon Mechanical Turk, we experimentally measure the effects of social influence on user decisions to recommend content. Specifically, after controlling for variation in content quality and position, we find that social influence affects outcomes of peer recommendation about half as much as position and quality do. These effects are somewhat correlated, increasing the inequality of popularity in the presence of social influence. Further, we find that social influence changes people’s preferences, creating a “herding” effect that biases their judgements about the content. While similar adverse outcomes have been noted in previous studies, we demonstrate a benefit of social influence: namely, it reduces the effort devoted to evaluating content without significantly diminishing the performance of peer recommendation.
I. INTRODUCTION

Every day people make a staggering number of decisions about what to buy, what to read, where to eat, and what to watch. The interplay between individual choices and collective opinion is responsible for much of the observed complexity of markets \[22\] and social behaviors \[20\]. Nowhere is this more evident than in peer production web sites, such as YouTube, Reddit, or Tumblr, which present far more content to users than they have time to examine. To help users identify interesting content, web sites often highlight a small fraction of their content based on the reactions of prior users. Such reactions include whether the user clicked on an item, downloaded it, recommended it or commented on it; actions that provide implicit rating of content quality. Some web sites also allow users to explicitly rate content. Based on this information, web sites may showcase highly-rated content on a special web page or simply order the content according to these ratings. In addition, some sites display the ratings to users, thereby providing explicit information about prior users’ reactions.

Understanding how people respond to this information will enable us to predict social behavior and even steer it towards desired goals. However, the implicit (through positioning) and explicit (through displayed ratings) signaling of the preferences of prior users creates synergies in people’s decision-making processes, which make it difficult to measure the relative importance of each method. An additional complication is that social signals can have multiple effects. By conveying information about which items others found interesting, signals could simply direct a person’s attention to items he or she may also find interesting \[13\]. Alternatively, as with peer pressure and social norms, social signals could change a person’s preferences, leading him or her to find some items more interesting than if the social signals were absent. In practice, these and other effects, such as novelty and content quality, combine to determine collective outcomes for the site. We disentangle some of these effects through controlled web-based experiments.

Multiple studies have examined how social influence affects the decisions individuals make in their daily lives, from what to buy to whether and who to vote for \[3, 10, 21\]. Even when it comes from anonymous people, social influence can bias individual judgements \[15, 17\], creating an “irrational herding” effect that amplifies small initial differences in individual response. The MusicLab study \[22, 24\] experimentally investigated the impact of social influ-
ence on cultural markets. These web-based experiments showed participants a list of songs and tracked which songs they listened to and which they liked sufficiently to subsequently download. The experiments varied the order in which songs were presented and whether or not participants saw the number of prior downloads, which served as a social influence signal. The study concluded that social influence was largely responsible for the inequality and unpredictability of song popularity, as measured by the number of downloads, although it did not attempt to control for the effect of song position.

To be influenced by a social signal, a person must first see it. Due to human cognitive biases, the presentation order of items strongly affects how people allocate attention to them [4, 18]. In an earlier experimental study using Amazon Mechanical Turk, we showed people a list of science stories and asked them to recommend ones they found interesting [14]. Participants were not aware of what others had previously recommended. We found that the ordering of stories significantly affected their popularity, i.e., how many recommendations they received. Ordering stories by popularity, as the MusicLab study did, led participants to focus their attention on the same few top stories, even though they were not aware of the ordering’s significance. This caused those stories to become even more popular than the rest, increasing the inequality of popularity. However, ordering stories randomly or by recency of recommendation led to more predictable and equitable outcomes.

In this work we extend the prior experiments to include social signals. We measure the degree to which information about the preferences of others affects the recommendations stories receive after controlling for their content and position within the list. We find that social influence is half as important as story position or content in explaining the variation in the number recommendations received by stories. In addition to examining changes in the outcomes of peer recommendation, we also study how social signals affect individual behavior, specifically, which stories people attend to and their preferences for them. We find that a large signal, indicating many others had previously recommended the story, may, to some extent, cause participants to rely on the signal, rather than personal judgement, to determine whether the content is interesting. This contributes to the “irrational herding effect”, as other studies have found [15, 17]. However, social influence also reduces the effort participants devote to evaluating stories, which may lead to greater efficiency in obtaining peer recommendations.
II. RESULTS

The social signals show users how many recommendations the stories received from prior users, i.e., their popularity, and have highly variable value (as described in Supplementary S1). To determine how much of variation in popularity is due to social influence, we must account for other factors that significantly affect recommendations. We quantify the effect of two such factors: story content and the position of the story in the list shown to a user.

A. Effect of Content and Position

Stories vary in how interesting they are to users. Users also vary in the effort they invest in evaluating content. Most users in our experiments chose to recommend stories based solely on the title and summary. Some users put more effort into evaluation by clicking on a story’s url to view the full story before deciding whether to recommend it. In our experiments about one quarter of the users clicked on at least one url. We distinguish these factors as story appeal and fitness. The appeal of a story is the likelihood a user who views its title and summary will vote for, or recommend, it: \( \Pr(\text{vote} | \text{view}) = r_s \) (whether or not they click on its url). The fitness of a story is the likelihood a user recommends it after clicking its url to see the full story: \( \Pr(\text{vote} | \text{click}) = q_s \).

Our experiments do not indicate which stories users view, so we cannot directly measure the probability a user views a story, \( \Pr(\text{view}) \), nor \( \Pr(\text{vote} | \text{view}) \) and \( \Pr(\text{click} | \text{view}) \). Instead, we use a model to jointly estimate views and story appeal, described in Supplementary S2. We find a wide variation in story appeal and a strong positional effect. Specifically, the model estimates that stories in top positions of the list receive about four times as much attention as stories in lower list positions, consistent with measurements reported in [14].

Our experiments record when users click on a story’s url to see the full text of the article. In these cases, we know both that the user viewed the story and whether that user subsequently recommended it. This allows directly estimating fitness, \( \Pr(\text{vote} | \text{click}) \), from the data. These estimates for the probabilities allow determining how users respond to variations in content (see Supplementary S2 C).
B. Social Influence and Outcomes of Peer Recommendation

We examine how social signals affect the outcomes of peer recommendation by comparing the number of votes stories receive in the experiments with and without social influence.

a. Inequality of Outcomes Stories differ in appeal; hence, when attention is distributed uniformly (as in the random ordering policy), we expect their popularity to vary in proportion to their appeal. Ordering policies that direct user attention toward the same set of stories will result in greater inequality of popularity. Social signals can further focus user attention, increasing inequality even more.

We quantify the variation in popularity by the Gini coefficient

\[ G = \frac{1}{2S} \sum_{i,j} |f_i - f_j| \]  

where \( S = 100 \) is the number of stories and \( f_i \) is the fraction of all votes that story \( i \) receives, so \( \sum_i f_i = 1 \). Figure 1 shows the values of the Gini coefficient in our experiments. The random ordering indicates the inequality due to variation in story appeal. The remaining conditions indicate the increase in inequality due to position bias and the influence signal. The figure shows that social influence increases inequality, for both the fixed and activity orderings.

b. Reproducibility of Outcomes For the activity ordering, the correlations between votes in the two parallel worlds is 0.78 and 0.63 without and with influence, respectively.
For the fixed ordering without influence we consider all users part of the same “world”. Nevertheless, due to the lack of history-dependence in this ordering, arbitrarily splitting the users in this experiment into two subsets gives, in effect, parallel worlds for this ordering. This gives correlation 0.87 between the worlds, compared with 0.90 for the fixed ordering with influence. These differences in correlations between parallel worlds with and without influence are not significantly different ($p$-value 0.5 for Spearman rank test). Thus, social influence does not appear to significantly degrade the reproducibility of outcomes in peer recommendation.

c. Story Appeal and Outcomes  One measure of performance of peer recommendation is how well the outcomes, i.e., number of votes, reflect the preferences of the user community. In our case, preferences for the stories are measured by their values of appeal. Position bias significantly affects how well users identify appealing stories and magnifies the inequality of outcomes beyond that expected from variations in story appeal \cite{14}. Figure 1 shows that social influence signals further increase inequality. This suggests that influence, like position bias, could degrade the relation between outcomes and appeal. However, we find this is not the case. Specifically, the correlation between number of votes and appeal is 0.77 and 0.79 for activity ordering, without and with influence, respectively. For the fixed ordering, these correlations are 0.45 and 0.34. Both cases are consistent with influence having no effect on this correlation ($p$-value 0.7 for Spearman rank test).

d. Strength of Influence and Outcomes  To separate the effects of influence from those of position bias and story appeal, we use the model (see Supplementary S2) to estimate the expected number of votes users would give to stories, based on their position and appeal, in the absence of a social signal. Comparing these estimates with the observed votes indicates how influence changes the outcomes of peer recommendation.

Quantifying the response as a function of the size of the social signal requires identifying how users attend to social signals. One possibility is users respond separately to each signal’s value. Alternatively, users could compare signals and focus on the rank of a story’s signal among all, or a sample, of the values shown. Another possibility is that users respond to signals that deviate by at least several standard deviations from the average signal value. In our experiments, these measures of signal strength are highly correlated (over 80%) and give similar indication of relative importance of appeal, position bias, and influence. So our
FIG. 2. Ratio of actual to expected votes for stories shown with each quartile of the influence signal. Error bars indicate 95% confidence intervals of the votes based on the number of instances in each quartile. There were 76110, 4273, 752 and 165 instances in the bottom to top quartiles, respectively.

conclusions do not depend on which of these, or similar, measures most closely reflects user behavior.

For definiteness, we focus on how votes depend on the signal value itself. Figure 2 compares observed votes to the expected numbers of votes those stories would receive when there is no social signal. Specifically, for each story \( s \) shown to a user at position \( p \), we use the model to determine the probability for that user to recommend that story as \( r_s v_p \), where \( v_p \) is the probability to view a story at position \( p \). We combine these values for all stories within each quartile of the full signal range in all social influence experiments. For each quartile, this gives the actual number of votes, the expected number and the number of instances (i.e., number of times a story was shown to users with a signal in each quartile). The figure shows the ratio of actual to expected votes, along with 95% confidence intervals estimated by treating each vote as an independent sample. Stories associated with signals in the bottom quartile get fewer votes than expected. Those with signals in the top quartile get about twice as many votes as those in the bottom quartile. This variation compares with the ratio of mean values in top and bottom quartiles of appeal (\( r_s \)) and position bias (\( v_p \)) of 3 and 4, respectively. Thus, social influence is responsible for about half the variation of popularity as that created by the differences in story content and position.

The increase in votes with the size of the influence signal raises the question of whether
the effect of the signal is more important as more users view the stories, and hence increase
the magnitude of the signal values, i.e., the number of prior recommendations for the stories.
Comparing responses by early (first 100) and late (subsequent) users in each experiment (see
Supplementary S1 C), indicates that a larger range of signals does not lead to a significantly
larger variation in response.

C. Social Influence and Individual Behavior

Social influence could increase the number of votes stories receive for two reasons. First,
by conveying information about the preferences of others, social signals may affect which
stories users attend to. Second, signals may change individual preferences in users’ evaluation
of stories [13]. To discriminate between these possibilities, we compare which stories users
choose to evaluate and, of those, which they choose to recommend for experiments with and
without influence signals.

e. Changes in Attention

We evaluate how influence changes which stories users attend
to by using url click data. Specifically, we examine how influence changes Pr(click|view),
using the model to adjust for position bias when determining the number of url clicks the
story is expected to receive in the absence of the influence signal (see Supplementary S2 B).
For each influence experiment we consider behavior starting after the 50th user, when there
is a significant history of prior votes on the stories. For each user, we divide the stories into
two groups: i) those whose signal is less than the median among the signal values shown to
that user, and ii) those with larger signals. Combining the expected and actual estimates
of Pr(click|view) for these groups gives values grouped by the relative strength of the signal
for each user.

Figure 3 shows the ratio between actual url clicks and those expected when there is no
influence. The figure shows two behaviors. First, the ratios are less than one, indicating
users tend to click on fewer stories when there is a social signal compared to experiments
without a signal. This indicates a change in user effort, as discussed below. Second, the ratio
is larger for larger signals, i.e., a user is relatively more likely to click on stories with larger
signals. Furthermore, the correlation between Pr(click|view) with and without influence
(both estimated as described in Supplementary Information Section S2 B) is 0.48, which is
FIG. 3. Ratio of actual to expected url clicks for stories shown with low or high signals to users (excluding the first 50 users in each experiment). Error bars indicate 95% confidence intervals of the ratios. There were 28713 and 32587 instances in the lower and higher groups, respectively.

nonzero ($p$-value less than $10^{-5}$ with Spearman rank test). This indicates that users have some tendency to click on the same stories, but with considerable variation.

f. Changes in Preferences

We determine how social influence alters individual preferences for stories from changes in probability to recommend a story conditioned on url click, $\Pr(\text{vote}|\text{click})$. In the absence of social signals, users recommend half of the stories they click on, $\Pr(\text{vote}|\text{click}) = 50\%$. This probability is higher with social signals: $66\%$, a significant difference from the no influence value (pairwise t-test $p$-value $5 \times 10^{-6}$). Moreover, the difference increases for larger signal values. For stories shown with influence signals below and above the median, we have $\Pr(\text{vote}|\text{click}) = 65\%$ and $75\%$, respectively, averaged over all stories. In other words, users are more likely to recommend a story they read when they see that many others have previously recommended it.

Social influence not only increases the probability of vote but also changes which stories receive votes: there is essentially no correlation between $\Pr(\text{vote}|\text{click})$ for influence and no-influence cases: the correlation 0.1 is consistent with no correlation (Spearman rank test $p$-value 0.5).

g. Changes in Effort

Social signals change the amount of effort users devote to the recommendation task. One measure of effort is the session time of each user, excluding the time required to read instructions and do the post-survey [14]. With influence, users spend, on average, about 40 seconds or $20\%$ less time on the task than users without the influence
signal. This difference is significant ($p$-value less than $10^{-10}$ with Mann-Whitney test).

Another measure of user effort is how often they click on a story’s url to view its content. For the roughly 25% of users who click on at least one url, we find a significant difference in the number of stories they click on. Specifically, without influence, such users click on 4.3 url’s, on average. With influence, they click on just 2.5, a significant reduction ($p$-value less than $10^{-4}$ with Mann-Whitney test).

In summary, social influence has three effects: (i) directing attention toward stories prior users have recommended, (ii) increasing user preference for the viewed stories, based on content of the stories in addition to their title, and (iii) decreasing the effort devoted to evaluating stories.

III. DISCUSSION

Our experiments quantified how social influence affects behavior in peer recommendation. The stronger the influence signal, the more likely the story was to be recommended than expected (based on its appeal and position in the user interface). However, influence was not as important as story content or position: compared to the variation in attention stories received simply due to their position, social influence accounted for half as much variance. While these differences did not significantly change the reproducibility of outcomes of peer recommendation, as compared to the no influence condition, they did produce more unequal outcomes.

Social signals changed not only which stories received more attention, but also how individuals evaluated stories. We found that people tended to recommend stories that others already found interesting. The larger the “peer pressure”, i.e., the larger the value of the social signal, the more likely the users were to vote for the story after reading the full article. In addition, users devoted less effort (both time and url clicks to view the full story) to the task when provided with social signals. This suggests users rely, to some extent, on the social signal, rather than personal judgement, to determine whether the content is interesting. This herding effect increased the inequality of recommendations among stories, well beyond that expected from variation in the appeal of the content itself and that due to position bias.
In spite of less user effort and larger inequality, the correlation between votes and appeal is similar with and without influence. Thus, showing users the social signal reduces the effort required to evaluate stories without substantially reducing the ability of the website to identify high-appeal stories. Therefore, at least with respect to this measure, the herding effect does not decrease the performance of peer recommendation systems. This contrasts with position bias which has a significant effect \cite{14}.

Integrating social influence into group decision making processes can lead to trade-offs in performance. While influence makes it easier for a group to achieve consensus and adopt new ideas \cite{21}, the bias it introduces into individual judgements may skew the outcomes of collective computation tasks that rely on independent decisions of many people \cite{13,17}. This is similar to the problem of adjusting for public information in crowd computation, for instance, by providing incentives for people to not only provide their own opinion but also estimate the opinions of others \cite{5,19}. However, our results show the benefits of social influence: by reducing effort, social influence makes it easier to collect opinions of more people, without significantly sacrificing performance of peer recommendation.

The experimental design using MTurk could be extended to address additional questions on how people respond to signals of prior users’ preferences. For instance, experiments could identify which aspect of social signals users primarily attend to (e.g., absolute value, rank or variation from average value for the stories), by manipulating the value of the signal shown to users. Results of such experiments could help develop a model of recommendation incorporating influence signal (cf. \cite{13}), and thereby suggest how peer recommendation performance would react to various choices for which signals to show users, and when.

IV. METHODS

We studied peer recommendation by conducting randomized experiments with participants recruited on Amazon Mechanical Turk (Mturk), a marketplace for work, which has also become a popular platform for experimental behavioral research \cite{2,7,11,16}. The experiments presented a list of science stories to people and asked them to recommend, or vote for, stories they found interesting. The interface displayed the title and summary of each story. The title was linked to the full story via its url. Thus people could read the full
story by clicking on the title, but were not required to do so. We refer to such actions as “url clicks”.

To investigate how social signals affect user behavior in peer recommendation, we extended the interface of the previous experiments to display, with each story, the number of previous users who recommended that story, starting from zero for all stories (see Supplementary S1). The user recruitment and vetting procedures were the same as the prior experiments [14].

In prior experiments [14] we measured how the position of a story affects how many recommendations it receives, and compared several policies for ordering the stories. For the present study, we considered two of these ordering policies.

First, the fixed policy showed all stories in the same order to everyone. This corresponds to the common practice on web sites of showing stories in a fixed order, e.g., chronological order to emphasize recent additions.

Second, the activity policy presented stories in chronological order of the latest recommendation they received, with the most recently recommended story at the top of the list. This is similar to Twitter’s policy of displaying the most recently tweeted or retweeted post at the top of the followers’ streams. By continually moving the most recently recommended stories to the top of the list, the activity policy creates a dynamic ordering that allows us to contrast competing effects of position bias and social influence.

In addition, as a control condition without the social influence signal, the random policy presented the stories in a new random order for each user, without showing the number of prior recommendations. This ordering effectively averages over the effect of position. We use this ordering policy to create a model of the effects of position bias and story content (see Supplementary S2).

The social signal shown to a given user depends on the actions of prior users. Thus repeating the same ordering policy with a different set of users can produce different signals. Moreover, the story order in the activity-based ordering depends on user actions. To evaluate the significance of this variation, we performed two independent, or “parallel worlds”, experiments for each ordering policy. Each parallel world starts from the same initial state: each story starting with zero recommendations and shown in the same order as used with
the fixed policy.

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SUPPLEMENTARY INFORMATION

S1. SOCIAL SIGNALS

Table S1 summarizes the experiments, showing the number of participants, the number of recommendations (i.e., votes) and url clicks for each condition. The random ordering policy is the control condition used to identify story appeal and the effect of position bias.

| ordering policy | users | votes | url clicks |
|-----------------|-------|-------|------------|
| random          | 199   | 1873  | 164        |
| fixed           | 217   | 1978  | 424        |
| activity        | 286 & 193 | 2586 & 1764 | 246 & 247 |

with influence signal

| ordering policy | users | votes | url clicks |
|-----------------|-------|-------|------------|
| fixed           | 192 & 211 | 1572 & 2057 | 125 & 135 |
| activity        | 200 & 210 | 1892 & 1959 | 113 & 144 |

TOTAL 1708 15681 1598

A. Display of Social Signals

Figure S1 shows a screenshot of the user interface, modified from the previous experiments [14] to indicate the number of prior recommendations (the social influence signal) for each story.

B. Evolution of Social Signals

The social signal shows users how many recommendations the stories received, i.e., their popularity. Starting from zero, the distribution of signal values develops a long tail as an experiment progresses: a few stories receive many more recommendations than the median. Figure S2 shows how the median and maximum signal values evolve in each experiment. The two parallel worlds of each ordering policy have similar ranges. The fixed ordering policy
FIG. S1. Screenshot of a web page shown during an experiment. The participant clicks on the button to the left of a story’s summary to recommend that story. The buttons include the number of prior participants who recommended each story. The colored graphic next to the fourth story indicates the participant has recommended that story.

FIG. S2. Median and maximum of the social signal, i.e., number of prior votes on all the stories, vs. number of users in the experiments with influence.

develops a more skewed distribution than activity ordering, with lower median but higher maximum values. This is because, due to position bias, users direct their attention to the same set of stories in the fixed ordering, exacerbating the “rich-get-richer” effect [14].

Since people tend to focus on stories near the top of the list [14], the effect of a social signal will likely depend on the positions of the stories with large signals. For example, Figure S3
shows the signal vs. story position for one user in each experiment. The high-signal stories appear in a wide range of positions in the activity-based ordering, while they are mainly concentrated near the beginning of the list in the fixed ordering. More generally, after 50 or so users made recommendations, the social influence signals in the fixed ordering are roughly sorted according to position in the list. Thus the signal reinforces the position bias. In contrast, by moving each newly-recommended story to the top of the list, activity ordering somewhat randomizes story positions, resulting in high-signal stories scattered throughout the list. The two activity experiments are qualitatively similar in this respect, but the precise positioning of stories with high signals and the actual stories differ between the two parallel worlds.

C. Evolution of Response to Social Signals

As experiments progress, the influence signal values get larger and distributed more broadly (Figure S2). If users respond primarily to the magnitude of the signal, the effect of influence would tend to become larger relative to other factors, e.g., position bias, as stories accumulate votes. To test this possibility, we compare response to the signal for the first 100 users in each experiment with those of the rest of the users. Specifically, Figure S4 shows the response measured by the ratio of actual to expected votes for each quartile of signal value occurring in our experiments. Early users encounter relatively small signals, in all cases within the bottom two quartiles of signal values appearing in the experiments. Nevertheless, such users have a similar change in response between the highest and lowest signals they encounter as shown by subsequent users who encounter the full range of signal
FIG. S4. Ratio of actual to expected votes for stories shown with each quartile of the influence signal to the first 100 users and the rest of the users in each experiment. Error bars indicate 95% confidence intervals of the votes based on the number of instances in each quartile. By comparison, Figure 2 shows the same values but aggregated over all users.

S2. MODEL

We use a simple model of recommendation that allows us to estimate the likelihood a user sees a story at a each position within a list. To recommend a story, a user has to both see it and find it appealing. Our model accounts for these two factors: the probability to view the story at position $p$, $\Pr(\text{view}) = v_p$, and its appeal $\Pr(\text{vote}|\text{view}) = r_s$. The model jointly estimates these factors from the observed recommendations and the positions at which each story was shown.

The model makes several simplifying assumptions to focus on the effects of story position on aggregate behavior of a user population. For instance, we assume a homogeneous user population, with no systematic differences between users in their preference for stories or how they navigate the list of stories. Therefore, the probability to view a story depends only on its position $p$ in the list. Moreover, the probability a user recommends a story after viewing it depends only on the story $s$ but not the user or the story’s position in the list. This assumption is reasonable since users were selected for their interest in science by the instructions. While there may be variations among user preferences, e.g., for technology or medicine, we focus on average behavior of users to identify the primary effects of different interfaces determining story position. Note that the model does not include social signals.
and their effects on users.

In addition, we assume that viewing each story is an independent choice by the user. This assumption was also used in a model of the Salganik et al. experiments [13]. This contrasts with models of list navigation (see e.g., [6, 9]) which posit that users view stories in order in a list until they decide to quit, so that viewing a story at position $p$ means all stories at prior positions were also viewed. While empirically we do not observe such sequential navigation, there is still significant dependence in viewing stories near a previously viewed one, which our model does not capture. Finally, we also assume that users consider each viewed story independently, in contrast, for example, to a dependence arising from users quitting after finding a few stories to recommend, in which case, whether a user views a story depends on the number of recommendations that user has already made.

Due to these assumptions, our model does not capture detailed behavior of individual users. Nevertheless, as shown in Supplementary S2 D, the model learned from one experiment can correctly predict the behavior of users in new experiments. Thus our simplifying assumptions allow understanding the effects of different choices of ordering stories shown to users.

Specifically, when story $s$ is presented to a user at position $p$ in the list (where $p$ ranges from 0 to 99), we model the probability $\rho(s, p)$ that user recommends the story as

$$\rho(s, p) = r_s v_p$$  \hspace{1cm} (2)

where

$$v_p = P(\text{view } s|s \text{ presented at position } p)$$  \hspace{1cm} (3)

$$r_s = P(\text{vote for } s|\text{view } s)$$  \hspace{1cm} (4)

**A. Parameter Estimation**

We do not directly observe values for $v_p$ and $r_s$ in the experiments. Instead we estimate these values by maximum likelihood. Specifically, with this model, the log-likelihood for user $u$ to recommend a set $S_u$ of stories is

$$L_u = \sum_{s \in S_u} \log(r_s v_p) + \sum_{s \notin S_u} \log(1 - r_s v_{p_s,u})$$  \hspace{1cm} (5)
with story $s$ shown to the user at position $p$. For a set of users $U$, the log-likelihood for all their recommendations is $L_{\text{full}} = \sum_{u \in U} L_u$. Since $r_s$ and $v_p$ enter the likelihood as products, there is an arbitrary overall scale factor $\alpha$, i.e., replacing $r_s \rightarrow \alpha r_s$ and $v_p \rightarrow v_p/\alpha$ for all stories and positions does not change the likelihood. To set the scale, we constrain $v_0 = 1$. The model predictions do not depend on the choice of $\alpha$.

Maximizing $L_{\text{full}}$ gives estimates for the model parameters, namely the story appeal $r_s$ for each story and position visibility $v_p$ for each position. Moreover, expanding $L_{\text{full}}$ around its maximum provides estimated confidence intervals for these parameters.

We used the random ordering policy with no social influence as the control condition training set for this estimation. To reduce fitting to noise, we used regularizers based on prior expectations that visibility changes smoothly with position in a list and the stories had similar appeal values. We used 10-fold cross-validation to determine the amount of regularization [1].

![Graph](image)

**FIG. S5.** Model estimates of story appeal, sorted in increasing order. Error bars give the 95% confidence intervals for all stories.

Figure S5 shows the $r_s$ estimates. These values vary by about a factor of five, indicating considerable variation in story appeal to the users. This confirms that our experiment design qualitatively corresponds to the large variation in preferences for content seen on social media web sites [8] and other domains, e.g., scientific papers [25].

Figure S6 shows the estimates for the probability to view the story $v_p$. As with direct measurements in the experiments [14], the probability to view a story decreases rapidly with its position: a story at the top of a list gets about five times as much attention as a story in the middle of the list. Thus, $v_p$ quantifies a cognitive bias known as “position bias” [18].
FIG. S6. Model estimates of story visibility, i.e., probability to view the story, as a function of story position $p$. Error bars give the 95% confidence intervals. The value $v_0$ is set to 1 by our choice of overall scaling, so it has zero confidence interval.

B. Estimating $Pr(\text{click}|\text{view})$

We use the model to estimate $Pr(\text{click}|\text{view})$ for each story, i.e., the probability a user clicks on a story’s url to read the full text of the story after viewing its title and summary. A user clicking to see the full text of a story necessarily first views it, so $Pr(\text{click}|\text{view}) = Pr(\text{click})/Pr(\text{view})$. We use the model’s estimate of the probability a user views a story at position $p$, $Pr(\text{view}) = v_p$. We define the indicator function $\chi(\text{click}; u, s)$ to be 1 or 0 according to whether user $u$ clicks on story $s$. We use data from all our experiments without social influence [14] to estimate $Pr(\text{click}|\text{view})$ for story $s$ as the average over users of $\chi(\text{click}; u, s)/v_{p_{s,u}}$ where $p_{s,u}$ is the position of story $s$ for user $u$.

C. Appeal and Fitness

Users tend to click on appealing stories: the correlation of $Pr(\text{click}|\text{view})$ with $Pr(\text{vote}|\text{view})$ is 0.46, which is unlikely to arise if there were no correlation ($p$-value less than $10^{-4}$ with Spearman rank test). This suggests that users evaluate an item’s appeal based on its title [13] (and summary when available) and then decide to proceed further with the appealing items, either by getting more information about them from the full text or immediately recommending them. This underscores the value of “first impressions”: users generally devote less effort to items whose titles (and summaries) are less appealing. In particular,
stories with the lowest quartile of appeal are, on average, less likely to get url clicks than stories with higher appeal.

The significance of basing most decisions on just a summary of each story depends on how well the summary indicates the fitness of the full content. In our experiments, appeal and fitness are only weakly related: the correlation between story appeal \( \Pr(\text{vote}|\text{view}) \) and fitness \( \Pr(\text{vote}|\text{click}) \) is 0.19, which is nonzero with marginal significance (\( p \)-value 0.03 with Spearman rank test). This relatively small correlation raises two possibilities: 1) the minority of users who click on urls may have systematically different preferences from the general population in our experiments, and 2) the appeal of a story, determined from its title and summary, is not a strong indicator of the interestingness of its full content.

To evaluate the first possibility, we divide the 199 users in the control (random-ordering experiment, without influence) into two groups: the 45 who click on at least one url, and the rest. We compare the votes of these two groups to see whether there are systematic differences in how these users evaluate stories. The correlation in the number of votes on the stories between the two groups is 0.5 and a \( \chi^2 \) test on the differences gives a \( p \)-value of 0.07 for the hypothesis of no systematic difference between the groups. Thus our data do not indicate systematic difference in preferences among these groups. This suggests the relatively low correlation between appeal and fitness reflects systematic differences between evaluating a story by the summary alone and by examining the full text.

D. Model Evaluations

To evaluate the model we use it to predict the number of votes stories receive under different ordering policies in the no-influence condition experiments. Specifically, we use all no-influence experiments other than those with the random ordering policy (which were used to estimate model parameters). This model test data contains votes made by 1319 users \[14\].

In addition to the fixed and activity orderings used in the influence experiments, this test data includes the remaining orderings from the prior experiments \[14\]. The popularity ordering presented stories in decreasing order of the number of recommendations they had received. Popularity-based ordering is widely used by web sites to highlight interesting
content. This ordering produced highly variable and unpredictable outcomes [14], because it tended to focus user attention on the same set of highly recommended stories, which became even more popular. The reverse policy inverted the order used with the fixed policy. For each of activity and popularity orderings, we conducted two ‘parallel world’ experiments [14].

We compare predictions of the model with three alternative baselines: APPEAL, POSITION BIAS and RANDOM. In the APPEAL model, position bias plays no role so users recommend stories based solely on how appealing they are. That is, the probability to recommend a story is independent of the position where that story is shown to a user, so Eq. (2) becomes $\rho(s, p) = V r_s$, where $V$ is a constant, equal to $\langle v_p \rangle$, the average value of $v_p$ over all positions.

In the POSITION BIAS model, users recommend stories based solely on their position, so $\rho(s, p) = R v_p$ where $R$ is a constant, equal to $\langle r_s \rangle$, the average value of $r_s$ over all stories.

In the RANDOM model, each story is equally likely to be recommended: $\rho(s, p)$ is a constant value, independent of story $s$ and the position $p$ that story is shown to a user.

These alternative models allow us to evaluate the relative importance of story appeal and position bias in producing the behavior observed in the experiments.

h. Aggregate Response Table S2 examines how well the model predicts the aggregate response, i.e., the total number of stories recommended by users under different ordering policies. The model overestimates the total response by about 10%, with somewhat larger error for the popularity ordering than for the others.

| ordering policy | relative error |
|-----------------|----------------|
| fixed           | −7%            |
| reverse         | −2%            |
| activity        | −7% & −5%      |
| popularity      | −13% & −11%    |

i. Response to Stories Figure S7 compares predicted and actual number of recommendations, i.e., story popularity, on all stories under different ordering policies. When different
FIG. S7. Prediction vs. actual number of recommendations for the stories for each ordering policy. The line indicates where the predicted and actual numbers are the same.

users see this story at positions $p_1, p_2, \ldots$, the expected number of recommendations, i.e., the model’s prediction, is $E(s) = \sum_k \rho(s, p_k)$ with $\rho(s, p)$ given by Eq. (2).

Table S3 quantifies the prediction accuracy for each ordering policy. This shows the model predicts the rank ordering of the number of recommendations fairly well. This could be useful for producing a ranked list of items, e.g., “best sellers” or “top hits”, rather than predicting their exact popularity. In addition, Table S3 shows the parallel worlds for the history-dependent orderings have consistent prediction errors.

In terms of the quantitative accuracy, predictions are usually within about 30% of the observed values, with some bias toward predictions above the actual values. The errors are similar for all the interfaces, indicating the model can compare outcomes irrespective of presentation order.

Even if the model’s predictions were accurate on average, there would be statistical errors. A quantitative measure is the number of standard deviations between the actual and expected values, i.e., $|A(s) - E(s)|/\sqrt{V(s)}$ for story $s$, where $V(s)$ is the variance in number of recommendations predicted by the model. The variance $V(s)$ arises from variations in votes given the values of $\rho(s, p_s)$, as well as from variation in the $r_s$ and $v_p$ values, indicated by the error bars in Figure S5 and S6. Variations in $r_s$ and $v_p$ values are correlated, precluding evaluating $V(s)$ by assuming independent variations. Instead we created 1000 samples from an approximation to the joint distribution of these values, with
TABLE S3. Prediction accuracy of the full model. The second column gives the rank correlation between actual and predicted numbers of recommendations. The third column is the mean value of the relative error, i.e., absolute value of difference between actual and predicted number of recommendations, divided by the prediction. The last column is the fraction of stories whose number of recommendations is within two standard deviations of the predicted value. For comparison, if votes were independent, the central limit theorem gives 95% for this fraction, which is close to the observed fractions.

| Ordering Policy | Rank Correlation | Relative Error | Fraction |
|-----------------|------------------|----------------|----------|
| fixed           | 0.85             | 0.40           | 0.90     |
| reverse         | 0.81             | 0.31           | 0.95     |
| activity        | 0.85 & 0.86      | 0.25 & 0.22    | 0.98 & 0.98 |
| popularity      | 0.89 & 0.90      | 0.27 & 0.29    | 0.95 & 0.91 |

Each sample a set of \( r_s, v_p \) values for all stories and positions, respectively. Specifically, the full distribution is proportional to the likelihood of the training set \( \exp(L_{\text{full}}) \). Our approximation is the multivariate normal distribution matching the quadratic expansion of \( L_{\text{full}} \) around its maximum. This captures the correlation among the values and closely matches the full distribution around its maximum, i.e., for values contributing to most of the probability. We simulated a set of votes on the stories for each sample. For story \( s \), the average number of votes in these samples is close to \( E(s) \) and their variance gives our estimate of \( V(s) \). Table S3 shows that over 90% of stories are within two standard deviations of the prediction. Thus the model not only predicts the outcomes, but the variance indicates the likely accuracy of the predictions.

For comparison, Table S4 shows the relative errors for the three baseline models: APPEAL, POSITION BIAS and RANDOM. The two baselines that ignore position bias give larger errors, whereas the model accounting only for position bias gives similar error. This indicates position bias is a major contributor to the variation in number of recommendations stories receive.

j. Which Stories Users Recommend. Our model assumes a homogeneous user population and that users consider stories independently. As discussed above, this simplification allows predicting how many recommendations a story receives, but prevents the model from
TABLE S4. Mean value of relative error in popularity predicted using baseline models.

| ordering policy | APPEAL | POSITION BIAS | RANDOM |
|-----------------|--------|---------------|--------|
| fixed           | 0.59   | 0.36          | 0.61   |
| reverse         | 0.55   | 0.40          | 0.55   |
| activity        | 0.30 & 0.27 | 0.27 & 0.28 | 0.39 & 0.39 |
| popularity      | 0.47 & 0.45 | 0.24 & 0.23 | 0.61 & 0.62 |

predicting the number of recommendations a specific user will make. In particular, user choices differ significantly from independence since we prompt users to make at least 5 recommendations if they make too few and we restrict consideration to users with at most 20 recommendations [14].

Nevertheless, the model does indicate which stories a user recommends when he or she makes a specified number of recommendations, $m$, for a specific story ordering. Specifically, Eq. (2) gives the probability for recommending each story. A simple measure of prediction quality is the fraction $f$ of the user’s $m$ actual recommendations that are among $m$ stories with the largest predicted recommendation probabilities. In the RANDOM model, each of the $\binom{n}{m}$ ways to pick $m$ stories from among the $n = 100$ stories in our experiments is equally likely. The probability that exactly $k$ of these choices match the user’s actual $m$ recommendations is

$$\binom{m}{k} \binom{n-m}{m-k} / \binom{n}{m} \quad (6)$$

Thus the expected value of the fraction $f$ in the RANDOM model is $m/n$.

Table S5 shows the median value of $f$ for the model test set. Thus, accounting for story appeal to the user community identifies considerably more of users’ recommendations than random-selection, and additionally accounting for position of stories shown to each user improves this prediction.
TABLE S5. Median fraction of user recommendations among the top predicted stories for each model.

| model          | 95% confidence                          |
|----------------|-----------------------------------------|
|                | median | interval |
| FULL           | 0.27   | 0.25     | 0.28     |
| APPEAL         | 0.18   | 0.17     | 0.20     |
| POSITION BIAS  | 0.27   | 0.25     | 0.29     |
| RANDOM         | 0.07   | 0.07     | 0.08     |