ABSTRACT
In social recommendation systems, users often publicly rate objects such as photos, news articles or consumer products. When they appear in aggregate, these ratings carry social signals such as the direction and strength of the raters’ average opinion about the product. Using a controlled experiment we manipulated two central social signals – the direction and strength of social ratings of five popular consumer products – and examined their interacting effects on users’ ratings. The results show an asymmetric user behavior, where the direction of perceived social rating has a negative effect on users’ ratings if the direction of perceived social rating is negative, but no effect if the direction is positive. The strength of perceived social ratings did not have a significant effect on users’ ratings. The findings highlight the potential for cascading adverse effects of small number of negative user ratings on subsequent users’ opinions.

Categories and Subject Descriptors
H.1.2 [Models and Principles]: User/machine systems — Human Factors; H.5 Information interfaces and presentation

General Terms
Design, Experimentation, Human Factors.

Keywords
Anchoring, recommender systems; social influence; social signals; theory-driven design.

1. INTRODUCTION
Extant research in recent years has demonstrated that people’s expressed opinions online can be influenced by what they perceive to be the behavior or opinions of others [11, 17]. In social recommender systems, where users can express opinions about objects they come across (e.g., photos, news articles, consumer products), the basic social information provided to users about others’ opinions, is the number of others as well as their “average” rating. Examples include information about up/down or like/dislike votes made by others. These basic elements of information – or social signals – often influence the signals’ viewers, who in turn often express their own opinions by rating, voting, or liking. Presented together, these social signals can be thought of as representing the direction of the social rating (i.e. whether, on average, others have positive or negative opinion about the object), and the social rating strength (i.e. how many personal ratings the average social rating is based on).

Our objective in this study was to identify and quantify the interacting effects of social ratings’ direction and strength on user behavior. We addressed the following research question: can we describe the mechanisms by which social influence shapes users’ ratings of objects online? And more specifically, what are the interacting roles of the social influence’s direction and its strength?

Using a web-based randomized controlled experiment, we sought to identify social influence patterns that are consistent across objects and user opinions.

2. INFLUENCE AND ANCHORING
Social influence its underlying mechanisms have been studied extensively in a variety of online settings [4, 7]. For example, [18], [16] and [14] showed that experimental manipulations arbitrarily signaling the seeming prior “success” of products on Kickstarter, downloadable songs, and articles on a social news aggregation website, respectively, led users to favorable online behavior toward these perceived “successes”. Furthermore, higher ratings on Yelp.com were found to lead to increased restaurants’ sales [3]. Social influence is often explained by a conformity effect, whereby people form or change their opinion or judgment when presented with a consensus, even when such consensus contradicts their own perception or opinion [19]. Therefore, good understanding of the mechanisms that determine social influence online is important for effective design and management of social recommendation systems.

By design, social recommender systems often give way to anchoring – users’ bias towards information that is available to them [13]. In numerous studies, anchoring was shown to influence people’s behavior. For example, exposure to high and low prices can influence the prices consumers would be willing to pay for products in related and unrelated categories [1]. Similarly, studies in law have found that among judges, anchors influence judicial decisions [9]. Similar findings were reported in other areas such as finance [12] and visual perception [10].

Researchers have largely focused on either the direction of the social signals – for example, whether the social ratings anchor users to a certain value or direction (e.g. positive vs. negative) – or alternatively, on the strength of these social signals, such as how strong the social consensus is, or how many others downloaded the song. For example, [7] found that when users of a movie recommender system were asked to re-rate movies while experimentally manipulated “predicted” rating were presented to them, they tended to change their rating toward the “prediction” anchor. More recently, [2] showed that users’ ratings are often influenced by a recommender system’s (experimentally manipulated) anchors, and that the effects of anchoring can be separated from the effects of the system’s perceived reliability.

However, social recommender systems often present simultaneously to users both the direction of the social signal (i.e. the average opinion of others, represented by their average ratings), and its strength (i.e. the number of others on which the average rating is based). Therefore, to examine the interacting effects of the social signals’ direction and strength on users’ ratings, we used a randomized experiment in which we manipulated the social ratings’ direction and strength attributed to a number of popular consumer products the experiment participants were exposed to, and
compared the product ratings provided by these participants. Our hypothesis, based on the prior research reviewed above, was that both the strength and the direction of the social signals will affect users’ opinions. In particular, our hypothesis was that the interaction between strength and direction will work such that the signals’ strength will moderate the effect of their direction. In other words, a strong positive social signal about an object will lead user to express, on average, a more positive opinion about the same object than when a weak positive signal is associated with it. Similarly, a strong negative social signal would have a more negative effect than a weak negative signal.

3. METHOD
Using a between-subjects experimental design (see Table 1), we explored behavior patterns that are consistent across different objects and different social rating levels.

<table>
<thead>
<tr>
<th>Social signal strength</th>
<th>Social signal direction</th>
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<tbody>
<tr>
<td>Weak</td>
<td>Weak-Negative: Negative social opinion based on few “others”</td>
</tr>
<tr>
<td>Strong</td>
<td>Strong-Negative: Negative social opinion based on many “others”</td>
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3.1 Participants and Data
Participants in the experiment were recruited from Amazon Mechanical Turk (MTurk) and asked about their opinions on a number of popular consumer products. Participants were paid $1.00 for their taking part in the study. All participants had at least 100 prior HITs of which at least 99% were approved, and were all from the US, based on the MTurk filter.

Participants were presented with images and names of five online and offline consumer products, one at a time and in a random order. The products included Cheerios, Gmail, Starbucks coffee, Twitter, and WhatsApp, selected for their popularity. Once they were presented with the products’ names and images, participants were asked to rate their familiarity with the product on a 1-5 scale, using a slider ranging between “Not at all familiar with it.” and “Extremely familiar with it.” The default value of the familiarity question was set at 5 and users could move the slider to the right (more familiar), to the left (less familiar), or leave it unchanged. The users then needed to click the Submit button to move to the next screen in which they rated products (see Figure 1). The familiarity question served two purposes: first, as an honesty check to screen out participants who might quickly click through the task without attempting to answer honestly. To screen out such data, in the analysis of each product we moved all product ratings from users who indicated a familiarity rating of 5 for the analyzed product. This way, we ensured that users had to make a deliberate choice. Second, the familiarity question helped us make sure that the products presented to users were across a wide range of familiarity levels.

Familiarity in itself was not part of our hypotheses, since causal relationship between familiarity and opinion are difficult to disentangle: it’s unclear if, for example, positive opinion leads to greater familiarity (I have a good opinion so I use it more) or if familiarity leads to positive opinion (by using it more I get used to it and develop a positive opinion on it).

3.2 Experimental Design
Participants could only take part in the experiment once, and were asked to rate each product in a separate product page, using a 1-5 star ratings (see Figure 2). In each product page, the participants were assigned to one of five experimental conditions: four were manipulated social signals, assigned randomly, in which information about the average rating of the product was presented next to the product image, together the number of ratings received by previous viewers (along the lines of UI design that are common to popular recommender systems such as Amazon or Netflix). A fifth experimental treatment served as a control condition, in which no social rating was presented to users. The ratings provided by users in the control condition served as a baseline against which to compare the effects of the social signaling experimental interventions.

![Figure 1. Social signals and user expressed opinion](image)

Social anchoring was used to represent to users the direction of the social ratings. To achieve this, we presented to the users consumer products next to their experimentally manipulated average ratings made by “other” participants in the study. These perceived ratings of “others” signaled the direction of social ratings, and were anchored in two opposing directions: a negative signal was represented by values ranging between randomly assigned 0.5-1 star (out of five possible), and a positive signal represented by values ranging between 4.5-5 stars randomly assigned for each product (see Figure 2).

The strength of the social ratings was manipulated by varying the number of “others” who seemingly rated the product (see Figure 2): the number of others was set at either a single-digit number of other raters, ranging between 3-7, representing a weak social signal, or a random high number (ranging between 3,000-7,000), representing a strong social signal. The difference in the strength of these chosen social signals values was shown in prior research to be perceived by users as representing significantly different numbers of raters [15].

We wanted all participants to interpret the social signals in a similar way. Therefore, the text “overall rating (based on N previous viewers)” was placed above the social rating (see Figure 2). The value of N presented to users changed between products and users, based on the experimental condition assigned.

In order to increase the perceived authenticity of the social rating the users viewed, we increased the variety of social opinions the
users we exposed to throughout their experiment interaction. To that end, we added two “dummy” popular products (Colgate toothpaste and Diet Coke) for which all values of the social signals’ direction and strength were different from the values assigned to the products included in the experiment. The social signal direction of these dummy products was set at 1, 2, 3 or 4 stars, and the signal’s strength at around 50 and 500 prior raters (non-rounded numbers were used). This addition ensured that under any experimental condition combination, no user will see the same social signals for all products.

In summary, for each product they rated, users were exposed to one of five experimental conditions - four interventions combining signal direction and strength (see Table 1), and a control condition.

4. RESULTS
Overall, 1040 people took part in this study. Their age ranged between 18 and 79, with the average at 34.7 (stdev = 11.7). 54.1% of the participants were women. Since ratings in which the users chose the default level of 5 as their familiarity level were removed from the statistical analysis, different products were analyzed using different sample sizes.

To explore the simultaneous effects of the direction and strength of social ratings, Analysis of Variance (ANOVA) was performed followed by Bonferroni corrections, to compare user ratings across the five experimental conditions for each product (see Figure 3).

Specifically, we compared users’ rating in the four intervention conditions with the control conditions. The following product-specific differences in user rating were found: for Starbucks coffee, we found a significant effect of Direction-Strength on user ratings (F (4, 962) = 4.24, p < 0.01). User ratings in the Weak-Negative condition were significantly lower than user ratings in the control condition (p<0.05). For Gmail, we also found a significant effect of Direction-Strength on user ratings (F (4, 880) = 6.81, p < 0.001). User rating in the Strong-Negative condition were significantly lower than ratings in the control condition (p<0.01). For Whatsapp, we found a significant effect of Direction-Strength on user ratings (F (4, 816) = 19.27, p < 0.001). Here, user ratings in both the Strong-Negative and Weak-Negative conditions were significantly different lower than ratings in the control condition (p<0.01 in both comparisons). Similarly, for Cheerios, we found a significant effect of Direction-Strength on user ratings (F (4, 1000) = 5.25, p < 0.001). User rating in the Weak-Negative were significantly lower than the ratings in the control conditions (p<0.05). Finally, for Twitter we found a significant effect of Direction-Strength on user ratings (F (4, 874) = 7.03, p < 0.001). The Strong-Negative condition was significantly different from the control condition with the average ratings in it lower than ratings in the control condition (p<0.01). To ensure that the effects observed were not a result of different levels of familiarity with the products, we examined the interactions between familiarity and signal direction, and found no significant effect on users’ ratings.

In summary, in all five products negative social signals led to significantly lower user ratings, whereas positive signals did not have any significant effect on user ratings. The size of the social signal was not found to effect user ratings.

5. DISCUSSION
By comparing users’ rating in four experimental conditions against ratings in the control condition, we were able to examine the simultaneous effects of perceived social ratings’ direction and
strength on users’ ratings (Figure 3). The findings point to two aspects of the relationship between direction and strength and their influence. First, there is an asymmetry between the effects of the positive and negative direction signal: a negative signal influences users’ expressed opinions in the expected direction (downward), but a positive signal did not lead to a similar effect in the opposite direction. This asymmetry trend was consistent across different products and varying levels of average product ratings. Second, the social signals’ strength was not found to have an effect on users’ ratings: none of the ten Strong-Weak positive and Strong-Weak negative pairs (i.e., two per product) exhibited significant differences between the weak and strong signals.

A possible interpretation of the asymmetry found between the effects of positive and negative social signals is that negative signals may be more persuasive than positive signals. Such a finding is consistent with prior research, and extends the research about the effectiveness of framing (i.e., the presentation of the positive or negative consequences of adhering to message recommendations), which found negative frames to be more persuasive than positive ones in the contexts of health behavior communication [6] and political campaigns [8]. It is also consistent with research showing that negative framing of messages can be more effective than positive one when the level of elaboration is low [5], as it is in many product rating settings.

The mixed findings of the effects of social signals’ strength may reflect the weight people attribute to the social signals’ strength. While somewhat surprising, it may be that users pay little attention to the number of others (as oppose to these others’ opinions). Additional research is therefore required in order to explore this possible explanation further, but more data supporting it may demonstrate that a small number of responders or commenters can relatively easily sway the expressed opinions of other users who view their responses. Some supporting evidence in this direction has been provided in prior research [14].

A limitation of this study stems from its experimental design: by exploring only two values for each of the strength and direction treatments, the scope of the findings is limited. Future work may address this limitation by examining a larger number of interventions, and in particular, additional combinations of signal direction-strength levels. This study nonetheless demonstrates the importance of considering both of these factors, simultaneously, in the design and management of social computing systems. Another direction for future work involves additional settings in which to explore direction-strength effects. The findings presented here will be more generalizable if similar patterns are to be found in settings such as news article comments, photos, and other settings where both social signals are presented to users.

Our findings have implications for designing and managing social computing systems. The asymmetry found in the effects of social ratings’ direction call for a careful use of social signaling, especially when such signaling is presented next to an online object at its early stages, when only few prior users have expressed their opinions about it. Initial negative social signaling may influence subsequent users and create a cascade of increasingly negative opinions. With respect to presenting social signals’ strength, the findings provide little support for the utility of presenting to users the number of prior raters.

6. CONCLUSION
In this work we examined the simultaneous effects of the signals of social ratings’ direction and strength on users’ ratings. We showed that the direction signal is influential, but only if it is negative, and that social ratings’ signal of strength does not affect users’ behavior. These findings highlight the potential effects negative social signals carry, and stress the need for designers of social computing systems to consider the risk of cascading negative input which may be self-reinforcing.

7. ACKNOWLEDGMENTS
This work was partially supported by NSF Award IIS 1149745.

8. REFERENCES