The Spread of Emotion via Facebook

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ABSTRACT
In this paper we study large-scale emotional contagion through an examination of Facebook status updates. After a user makes a status update with emotional content, their friends are significantly more likely to make a valence-consistent post. This effect is significant even three days later, and even after controlling for prior emotion expressions by both users and their friends. This indicates not only that emotional contagion is possible via text-only communication and that emotions flow through social networks, but also that emotion spreads via indirect communications media.

Author Keywords
Computer-mediated communication; emotional contagion; emotion; Facebook; social networks

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

General Terms
Human factors, measurement, languages, verification

INTRODUCTION
Emotional contagion is the process by which people "catch" emotions from each other. This process, which can be as simple as becoming happier in the presence of a smiling friend, is important to psychological and physiological functioning, and vital for healthy relationships [1,12].

Prior research suggests that nonverbal communication is the means by which emotions are contracted. Some research even claims that nonverbal cues are "necessary" for contagion [1,5], but this may not be the whole story: Recent papers indicate that emotion can be contracted through computer-mediated communication (CMC) systems [8,9] in a similar manner to the emotional contagion traditionally observed during in-person interactions [10,11,12]. Overall, emotional contagion has been demonstrated in real life, in laboratory settings, and most recently via CMC.

This is especially important as human social relationships and interactions have been moving into the online world in the form of social networking sites (SNS), and are being increasingly supported via CMC. Facebook, a very popular SNS claiming over 800M users as of publication, is a common means by which people interact with each other both directly (such as via messages, chatting, wall posts, comments), and indirectly (such as via status updates).

In this paper, we examine an important implication of emotional contagion theory: whether and how emotions "spread" via SNSs. The examination of how emotions spread through a textual medium such as an internet SNS is very interesting: If such a process can be shown, this provides evidence for basic psychological processes re-exhibiting themselves in new media, and also contributes to a growing body of evidence suggesting that interaction with "friends" on SNSs mirrors the manner by which people interact with others in offline life [4,10].

Though the current studies are correlational, they address several confounds in prior results by making use of the undirected nature of Facebook "status updates:" Prior research on emotional contagion has usually examined situations in which the expresser and observer of an emotion are communicating directly. In that case, the process by which the emotion is transmitted is ambiguous. For example, in the case of a positive emotion such as joy, the observer is faced with a joyful communicator. If they then become joyful themselves, is it direct transmission of the partner's joyfulness, or simply a peripheral effect of having a joyful interaction? Happier individuals are more expressive, creative, and generous [7], suggesting that interacting with an individual in a good mood would be a pleasant experience—and thus explain increased positive mood. Conversely, would an angry communicator cause anger in a friend through negative, angry interaction, or would the friend become angry merely because of emotional contagion? Further, even if emotion is not actually felt by the conversant, disclosure norms may require that they respond in a similar manner. By examining status updates, which are not specifically "directed" towards a conversation partner (their "friend," in the Facebook case), any observed effects should not be due to effects of proximal communication.

There are still concerns that disclosure norms may affect valenced responses on SNSs, as people strategically present themselves to others in order to achieve certain social goals [18]. However, others have shown both that Facebook profiles seem to reflect actual personality rather than idealized forms ([1], which also reviews the literature on presentation), and "word count" methods of examining

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natural language production are largely immune to self-presentational concerns [15]. Thus, our strategy to evaluate the downstream emotion expression by the friends of those who express emotion: Examination of status updates. To reduce social demands, we examine emotion expression by users via their undirected updates, and to control for self-presentation, we evaluate emotion expression by those users' friends similarly.

A second confound present in emotional contagion research is the possibility that emotions are not actually being "contracted," but that a single event is causing emotion in both parties. For example, if I am happy because my paper is accepted, and I share this with a friend, the friend may become happy because my paper was accepted (and not simply because I am happy). Similarly, mere exposure to a certain writing or self-expression style in the Facebook feed may lead to conversational mimicry despite the undirected nature of the communication. To address this potential confound, we utilize a multi-day lagged regression design. We predict that when users use positive or negative words (i.e., express positive or negative affect [13]), their friends' emotional states will be affected: Those friends will express more of the corresponding emotion (i.e., use positive or negative words in subsequent updates). In order to address the "same event" confound, we examine their friends' use of positive words on the same day, but also on the two subsequent days, using the days in between as statistical controls. The end analysis, then, examines a three-day lagged effect: If a user posts a positive update today, is the user's friend more likely to post a positive update three days from now? If they are yet more likely to do so than we would expect, given all the words used by both users and friends in the subsequent days, we suggest that the "shared experience" confound is eliminated, as any shared emotional experience would be encoded into the language of both on the same timescale.

Though this research is correlational and thus cannot be argued to represent "contagion" of emotion, showing that emotion spreads through SNSs despite these confounds controlled tests a key corollary of emotional contagion theory and motivates future experimental work.

In sum, we predict that when a user uses an emotion word in a status update, their friends will be more likely to do so subsequently, in a valence-consistent way: If a user uses positive words, their friends will be more likely to use positive words as well (and less likely to use negative words), and vice versa.

METHOD

Participants

Participants were classified into two groups: First, the "users" group was comprised of the set of all active Facebook users who chose to view Facebook in English and who posted at least one status update on three consecutive days (in order to control for subsequent posts when conducting the three-day analysis). From this group of users, one million were chosen at random. The second group of participants was the English-speaking set of these users' friends, consisting of approximately 150m users.

From these users and friends, we then selected a random subsample of users (and all of the friends of those users) that together occupied approximately 5 million rows of data for analysis, in order to produce a set that was appropriately sized for analysis using modern statistical software. This end result constituted a sample of $n = 61{,}289$ users.

It is important to note that we did not systematically include or exclude friends from analysis based on what those friends saw or commented on. In other words, we examine posts by friends, whether or not they saw the users' initial post, as doing so would not be computationally feasible: A single view of one's newsfeed might produce 5 viewed posts, with many more appearing on each page-down. However, this inability does not confound our results as there is little reason to expect that a friend's expression of emotion would somehow be affected by updates they did not see; rather, it constitutes error that should make it more difficult to find statistically significant results.

Procedure

As in [13], all status updates posted by both users and friends during a three-day window were processed using the list of positive and negative emotion dictionaries from LIWC 2007 [15], using the Hive database system [18], which allowed for parallel computation in order to complete the word-counting task rapidly. Use of the LIWC software package itself was not possible as these status updates constituted far more data that would fit on a single contemporary computer. Because this work was completed in an entirely computational manner, no researchers ever saw any user-generated text in an identified form[1], in compliance with Facebook's Terms of Service [6].

RESULTS AND DISCUSSION

To test our hypotheses, we predicted word usage (positive or negative) by friends from word usage (ibid), by users. This was done using "Hierarchical Logistic Regression," a system similar to the now-common "hierarchical linear modeling" techniques, but adapted to use a logistic regression model. This multi-level technique was necessary because users have different numbers of friends. This analysis was completed using the "glmer" function in the lme4 library for R [3,16].

Same-day analysis

Our analysis was tiered based on the day of prediction: For our first analysis, we predicted whether a friend would use

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[1] More specifically, researchers did not see any user-generated text that they would not otherwise have been able to see; procedures were validated via analyses of the researchers' own status updates.

a positive word if the user used a positive word on the same day. This effect was significant and positive[2], $\beta = 0.076$, $z = 24.98$, $p < .001$. We replicated this effect by examining the corresponding effect for users and their friends on all three days of data collection; these effects were all significant and in the same direction.

Single-day lag

Examining only the first day's worth of data, however, is not sufficient to draw strong conclusions. For example, many people may share common interests and be aware of the same goings-on in the world around them. This could lead to a "third variable" problem, in which a single event (say, a college football team winning a game) or a homophily effect (i.e., happier people having happier friends) would make both users and their friends happy. To address this issue, we predicted friends' word usage on Day 2 instead of Day 1, using their own words on Day 1 and the users' words on Day 2 as controls: Thus, the question becomes "does a user's emotion expression on Day 1 predict their friends' emotion expression on Day 2 *above and beyond* their friends' emotion expression on Day 1." For this analysis, we hypothesized that users' words on both Days 1 and 2 would be significant and positive predictors of friends' words on Day 2, but that the coefficient for the same-day effect would be larger than the prior day's.

These hypotheses were supported: Controlling for friends' and users' words on Day 1, users' words on both Days 1 and 2 still predicted friends' words on Day 2, β's = 0.046, 0.050, z's = 16.0, 17.7, p's < .001, respectively, and with the same-day coefficient being larger than the prior day's. In this model the friends' own words on Day 1 were also significant (and much stronger) predictors of word use on Day 2, $\beta = 0.931$. As above, this effect was replicated using data for Days 2 and 3 instead of Days 1 and 2; effects were similar (β's = .051, .053, and .961 respectively; p's < .001).

Two-day lag

Finally, we took this analytic process one step further, predicting friends' word use on Day 3 from users' word use on Days 1, 2, and 3, controlling for their own word use on the two prior days. As predicted, all three coefficients were significant: Friends' word usage was predicted by users' word use on Day 1 ($\beta = 0.031$), Day 2 ($\beta = 0.037$), and Day 3 ($\beta = 0.040$), as well as their own word use on Day 1 ($\beta = 0.743$) and Day 2 ($\beta = 0.824$); all p's < .001.

Negative words

We then took the same approach to the analysis of negative words; all effects across all replications were significant, with even larger effect sizes: β's were all positive and p's < .001; β's around 0.092 for same-day analysis; around 0.053 (users' words on Day 1) and 0.058 (Day 2) for single-day lag; and 0.0384 (Day 1), 0.0379 (Day 2) and 0.0367 (Day 3) for two-day lag.

Emotional suppression

Finally, we examined what we call "emotional suppression," with "suppression" taken as the opposite of "spreading:" Whether using *positive* words would decrease friends' use of *negative* words, effectively *suppressing* the counter-valenced emotion, or whether using negative words would similarly suppress friends' positivity. To examine this effect, we fit two additional two-day lag models as described above: One predicting friends' positive emotion word usage and one predicting friends' negative emotion word usage. In this analysis, however, we used all of the inputs as predictors: Both positive and negative word usage by users on Days 1 through 3, and both positive and negative word usage by friends on Days 1 and 2.

As expected, we observed a cross-valence suppression effect, in which users' use of negative words suppressed use of positive words by friends over the three day time period, β's = -.015, -.013, -.011 for Days 1-3, and users' use of positive words buffered their friends against negativity over the same timeframe, β's = -.022, -.013, -.016, all p's < .05.

GENERAL DISCUSSION

Over the course of several analyses of a very large data set, we show a consistent pattern: When a Facebook user posts, the words they choose influence the words chosen later by their friends. This effect is consistent with prior research on emotional contagion, in that the friends of people who express emotional language end up expressing more same-valenced language as well. We have also shown preliminary evidence for what might be called "emotional suppression," in which the use of positive (or negative) words buffers users' friends against negativity (positivity).

These effects are present despite the fact that we operationalized emotion as the use of an emotion word in a status update, which was not directed from "users" to their friends, who may not have seen the initial update, and whose subsequent updates were not "responses" to the initial updates, and were persistent even three days later.

The implications of this research are highly suggestive: It supports years of research into emotional contagion processes [12], suggesting that certain supposed confounds may not fully explain the effect. Further, these results suggest that posts to Facebook have the ability to affect our friends' subsequent posts. This is *not* to say, however, that they affect our *friends;* further research is necessary to make this claim. Even if they did, however, we would not advise Facebook users to go around expressing disingenuous positivity or to suppress the expression of negative emotions in order to keep one's friends happy: The psychological history of humans likely indicates that these expression strategies probably help us to remain psychologically healthy, by allowing others to share in our joy and helping us recruit social support from our friends

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[2] β here is a logistic regression "log-odds" coefficient: $\beta = .076$ means that positive posts by users predicts friends' likelihood of doing so to become $e^{0.08} = 1.08$ times larger.

when needed. Sharing negative emotions may also be important for building feelings of closeness [10].

CAVEATS AND FUTURE DIRECTIONS

The current study does not permit the causal conclusion that emotions in friends are caused by emotions in users. This would require an experimental approach, rather than the current correlational design. One could also argue that our effect sizes are quite small (or perhaps even trivial): Our smallest significant effect size was a mere 1.1% decrease in friends' likelihood of using negative words when a user uses a positive word. We note, however, that word usage is a rather noisy measure of emotion: Prior research has shown significant (but small to moderate) correlations between word usage in status updates and overall positivity (e.g., [13] showed only $r = 0.17$ with Satisfaction with Life). Additionally, we were unable to exclude "friends" from analysis when they had not seen the users' posts, further reducing our observed effect size. However, we observed a high frequency of emotionality in updates: 55% of updates contained a positive word, and 34% contained a negative word. These high rates suggest that even low rates of "spread" may indeed be meaningful.

The "bag of words" approach also comes with its own disadvantages: We did not explicitly exclude negations or conduct a revalidation of the LIWC [15] dictionary, which may increase the noisiness of the LIWC analysis. However, we argue that while these effects are small, they are not trivial considering the enormous scale of SNS usage: In a domain as large as Facebook, if expressing positivity on one day causes one out of 100 friends to post positively three days later (when they otherwise would not have), then the tens of millions of people posting each day may be responsible for hundreds of thousands of positive posts that would not have otherwise occurred, and which in turn could cause thousands more; we do not consider this trivial.

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