In the Mood for Being Influential on Twitter

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In the Mood for Being Influential on Twitter

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***Abstract*—Researchers have widely studied how information diffuses in Twitter and have often done so by modeling the social-networking site as a communication graph in which tweets spread depending on its nodes' graph properties (e.g., degree, centrality). The resulting models are tractable but make a crucial assumption: that the human being behind an account is a node and that, consequently, human expression in Twitter can be modeled as a set of abstract nodes communicating with each other. We set out to test whether Twitter users can be reduced to look-alike nodes or, instead, whether they show individual differences that impact their popularity and influence. One aspect that may differentiate users is their character and personality. The problem is that personality is difficult to observe and quantify on Twitter. It has been shown, however, that personality is linked to what is unobtrusively observable in tweets: the use of language. We thus carry out a study of tweets - more specifically, we compare five different categories of user (one of which is influencer) and look at their language use. We find that popular and influential users linguistically structure their tweets in specific ways, and that influential users tend to be individuals who express negative sentiment in part of their tweets. These findings suggest that the popularity and influence of a Twitter account cannot be simply traced back to the graph properties of the network within which it is embedded, but also depends on the personality and emotions of the human being behind it.**

***Keywords*-Web 2.0, Language, Social Networks, Twitter**

I. Introduction

Models of information diffusion in Twitter assume as little as possible about what a Twitter account is and, that way, they are easy to understand and are tractable: the diffusion of a user's tweets largely depends on the user's graph properties - on whether the node has central position in the graph or lies at its periphery [6], [22].

In so doing, the human being behind an account is reduced to an abstract node in a graph: as Zadie Smith writes, "Everything shrinks. Individual character. Friendships. Language. Sensibility" [28]. In general, before modeling a macro property like social influence, one should understand that property's micro-foundation. In Twitter, this translates into modeling the (macro) emergence of influence only after understanding the (micro) interactions between users. This is necessary because, with *macro* models at hand, one cannot make definite assertions about *micro* interactions between users. To see why, consider that, based on a macro analysis of the Twitter graph, one should conclude that "Twitter is not a social network but a news media" [17] - the graph does not show any of the characteristics that are typical of a social graph (e.g., shortest path, clustering coefficient). While a (macro) graph analysis suggests that Twitter is not a social network, recent (micro) studies counsel caution. These studies went beyond a graph analysis and analyzed the activity of individual Twitter profiles (i.e., who replies to whom, which relationships are mutual, which tweets are passed on) and found that the social media site can be classified as a set of real communities according to well-established sociological definitions of community. Indeed, Twitter profiles are the basis of communities in which users regularly meet, talk, provide support and help each other [1], [10] and exhibit characteristics of McMillian and Chavis' "sense of communities" [19], in that users display a sense of belonging and have the ability to influence each other through their replies and retweeting.

Following up this previous work on micro interactions, we consider the main element that mediates interactions between users - the use of *language* in their tweets. More specifically, we will compare five different categories of user (one of which is influencer) and looked at their language use. As we shall see in Section II, previous work on Twitter has not considered the relationship between the use of language and influence. Given the importance of this relationship (which we will detail in Section III), we set out to study it and, in so doing, we make two main contributions:

- After crawling 31.5M tweets, we analyze them using the "Linguistic Inquiry Word Count" (LIWC), a dictionary of English words that reflect people's emotional and cognitive processes, and study the relationship between language and five different types of users (Section IV). These users include popular users (i.e., those who have many followers), stars (i.e., those who follow few but are followed by many), and influential (i.e., those whose content is acted upon)[1].
- We verify an hypothesis, previously tested only on small studies conducted in behavioural laboratories, that establishes a relationship between expressed sentiment and influence in Twitter (Section V). In particular, we show how influential users tend to be individuals

[1]Despite analyzing 31.5M tweets in general, only a limited number of those tweets is available for some user types. For example, 192K tweets can be associated with those who are considered influentials according to a score called TrstRank. That is because the score is defined only for 1K users in our sample. However, as we shall see, this will not affect the statistical confidence of our results.

who express negative sentiment in part of their tweets - whereby negative mood has been previously found to have desirable effects on problem solving, idea production, and social influence.

We finally discuss both theoretical implications of our findings on social influence in Twitter, and practical implications for social media marketing (Section VI).

II. Existing Work on Social Influence

There are two contrasting views on social influence. The first posits that influentials are special individuals with well-developed persuasion skills, so the extent to which a rumor will spread can be predicted based on its initiators. This idea has been most popularized by Malcolm Gladwell's "The Tipping Point" [9] - this book argues that social epidemics are initiated by a tiny minority of individuals who are unusually persuasive or well-connected. This argument is based on a theory called the "two-step flow of communication" [14] - information flows from the media to the influentials and from them to everyone else. The consequence is that, by reaching a small number of influentials, one is able to trigger a viral campaign at little cost.

The second view on social influence claims that anyone can be influential and rumors spread only if there is societal willingness to accept them, so the extent to which a rumor will spread cannot be predicted based on its initiators and is thus accidental. Duncan Watts uses the terms "accidental influentials" as he considers social epidemics to be "mostly an accident of location and timing" [32]. This is because, after simulating a large number of social network configurations, he and his colleague found that epidemics are not triggered by a few influentials but, rather, by a critical mass of easily influenced people [4]. The researchers consequently took a dim view of social media marketing and concluded that word-of-mouth marketing strategies should stop focusing on finding supposed influentials.

In Twitter, however, empirical evidence predominantly supports the idea that influentials are not accidental, but rather individuals who exhibit specific behaviours. For example, Cha *et al.* describe influentials as individuals who keep great personal involvement and who limit their tweets to a single topic, and can be thus identified [2]. More recently, Romero *et al.* found that influentials are highly-active users and consequently defined a new influence measure based on user activity - this measure accurately predicts URL clicks (hence influence) on Twitter [3]. All of this goes to show that influence on Twitter is not gained accidentally but strongly depends on audience engagement. No study has yet established what type of engagement translates into influence. Since engagement is also expressed through language, we choose to analyze the use of language and detail why we do so next.

III. Why Language

We are interested in the use of language because its analysis is *unobtrusive* and has been shown to be *insightful*, all the more so in Twitter, as we shall claim in this section.

Unobtrusive Word Analysis. The use of language has been extensively studied in controlled experiments in which human subjects were asked to perform a variety of speaking and writing tasks and researchers then manually processed the responses of participants. This processing translated into extensive and laborious transcriptions and has been consequently replaced by electronic experimental settings. However, there remain still two types of biases in such experiments nowadays: 1) *sample bias*: experimental subjects have often been undergraduates of White, Educated, Industrialized, Rich and Democratic (WEIRD) countries [13]; 2) *response bias*: people might perform tasks in the behavioral laboratory differently than how they would 'in the wild' (Hawthorne effect [18]). One of the strengths of the research we set out to conduct is that Twitter *partly* reduces both biases in that representative user samples can be extracted (reduced sample bias) and tweets can be captured unobtrusively (with lack of experimental demands resulting in no response bias).

Insightful Word Analysis. In addition to being unobtrusive, word analysis in Twitter meets our research goal: that of testing whether users are look-alike nodes in a graph, or whether they show important (linguistic) differences. To see why, consider that, given two individuals, one aspect that is likely able to differentiate them is personality, and it has been shown that one's personality traits greatly influence one's use of language. To a certain extent, our words reflect ourselves [12]. The number of first-person pronouns (e.g., I, my) in speech or writing often correlates with narcissism and with the personality trait of "Neuroticism" [29], [33]. Second-person pronouns (e.g., you) and third-person pronouns (e.g., she, they) are markers of social engagement and negatively correlate with depression [27]. Furthermore, words that express positive emotions (e.g., good, happy) are used more by extroverts than introverts [23]. Given the importance of language, as user-generated content becomes increasingly available on social media, studies on the use of language in these media are bound to appear more and more frequently in the literature.

IV. Proposal

To determine whether different types of individuals (e.g., popular, influential) use language differently in their tweets, we follow four steps: 1) crawl a large number of tweets; 2) determine the use of language in those tweets; 3) classify users into five types; and 4) test whether there are linguistic differences among the five user types.

Categories	Example of words	Description
first person	I, my, me	Self-focus
second person	you, you'll	Express one-to-one engagement
third person	she, their, them	Express sense of community
cognitive	cause, know, ought	Preference for cognitive processes
time	hour, day, o'clock	Express temporal context
past verbs	walked, were, had	Concerned with the past
present verbs	walk, is, be	Concerned with the here and now
future verbs	will, might, shall	Concerned with the future
posemo	happy, pretty, good	Express positive emotions
negemo	hate, worthless	Express negative emotions

Table I
CATEGORIES THAT REFLECT THE USE OF LANGUAGE AND OFTEN CORRELATE WITH DIFFERENCES IN PSYCHOLOGICAL PERSONALITY.

Step 1: Crawling tweets. To control for any variability in the use of language across countries, we preferentially chose Twitter profiles from the UK and did so as follows. We chose a small set of popular London-based seed profiles of UK-based news outlets. These were: Metro, a free newspaper circulated primarily in London and a further 13 urban centres across the UK, with a readership of some 3.5 millions; The Independent, a center-left newspaper with a circulation of around 651,000 a day; and The Sun, a tabloid with a circulation of some 3 million copies daily. These news outlets were chosen because they cover the entire UK political spectrum and have high penetration rates in the city [26]. Each Twitter user that follows these profiles was crawled. Their tweets were captured using Twitter's Streaming API between the dates of 27 September and 10 December 2010, collecting at most 200 tweets for any one user (200 is the limit set by the API). This resulted in a dataset of 250K Twitter profiles and 31.5M tweets.

Step 2: Determine the use of language in tweets. To analyze the tweets, we use a dictionary called "Linguistic Inquiry Word Count". LIWC is a standard dictionary of 2,300 English words that capture 80% of the words used in everyday conversations and reflect people's emotional and cognitive perceptions. These words fall into 72 categories, such as positive and negative emotional words, and words about work, school, money. Note that, rather than grouping words based on their material subject matter (e.g., 'sports', 'technology'), LIWC categories are generally abstract, and are based on linguistic and psychological processes. For example, there exist categories for cognitive processes (such as 'insight' and 'certainty'), psychological constructs (e.g., affect, cognition), as well as personal concerns (e.g., work, home, leisure activities). Each word may thus belong to multiple categories; for example, the prefix entry 'hostil*' belongs to the categories 'affect' (affective processes), 'negemo' (negative emotions) and 'anger'. Ten of those categories (reported in Table I) have been found to correlate with personality traits [8], [20], [21]: the use of words in the category 'negative emotions' is associated with the personality trait of "Neuroticism", while the use of words in the category 'positive emotions' is associated with "Extraversion", for example. Thus, for the tweets in each profile, we need to count the number of words matching the ten categories. Before doing so, we process tweets as follows: firstly, the text is converted to lowercase and tokenized around both whitespace and common punctuation. Any token with a leading '@' is discarded, as this is simply the username of another Twitter user. Each token is then stripped of its remaining punctuation, and compared to a list of common English stopwords (specifically, those used by MySQL 5.65[2]), as well as a list of Twitter-specific stopwords (such as "rt", which is a common token signifying that the tweet containing it is a re-tweet, and has been forwarded on from another Twitter user). All non-stopword tokens are retained. For each profile, we then count the number of words matching the ten categories and compute the normalized fraction of each category's count (let us call it *normalized count* for category c):

$$f_c = \frac{w_c - \mu_c}{\sigma_c} \tag{1}$$

where w_c is the fraction of words classified in category c (over the total number of classified words) for the profile; μ_c is the fraction of words in category c, averaged across all profiles; and σ_c is the corresponding standard deviation.

Step 3: Classify users into types. The two main types of users whose linguistic behaviour we are interested in are popular users and influential ones. Meeyoung Cha *et al.* and Daniel M. Romero *et al.* have independently found that a user's *popularity* highly correlates with the number of followers, and that a user's *influence* correlates with audience engagements (measured based on mentions and retweets) [2], [3]. To determine who the popular users are, we can simply look at the number of followers they have, information that is ready available from their Twitter profile. To determine whether a user is influential, we use two third-party applications that are well-established among social media analysts: Klout (klout.com/) and TrstRank (http://api.infochimps.com/describe/soc/net/tw/trstrank). Klout fully ignores a user's number of followers and number of tweets and, rather, considers the extent to which the user's content is "acted upon", that is, whether it is clicked, replied, and retweeted [15]. Trstrank measures the importance of a user based on the user's PageRank centrality on the Twitter graph [31]. Klout scores are defined for 174,881 users of the 250,000 we crawled (Klout is not able to define any score for the remaining 32% of users); TrstRank scores are determined for 1,021 users (the number of users has been

[2]http://dev.mysql.com/doc/refman/5.6/en/fulltext-stopwords.html

User Type	Description
Popular	Followed by many (high $followers$)
Influential	High $Klout$ and $TrstRank$ scores
Listener	Follows many (high $following$)
Star	Follows few and is followed by many (high $\frac{followers}{following}$)
Highly-read	Listed in many reading-lists (high $listed$)

Table II
TYPES OF TWITTER USERS UNDER STUDY.

considerably lowered by technical limitations imposed by the commercial service). However, despite a smaller sample size for TrstRank scores, we will see in the next section that there are still quite a few correlation coefficients (relating users' types to language use) that are statistically significant. In addition to classifying users into *influential* and *popular*, we consider the statistics readily available on Twitter (what the social-networking site calls 'following', 'followers', and 'listed' counts) and identify three further types of users: *listeners* (those who follow many users), *stars* (those who follow few but are followed by many), and *highly-read* (those who are often listed in others' reading lists). We thus have a total number of five user types (Table II) that we are now able to study.

Step 4: Determine whether there are linguistic differences among the five user types. The characteristics of the medium and its user demographic might impact the use of language on it. Indeed, tweets are text-based posts set to 140-character limit, so immediacy of communication is required. Also, users reflect a specific demographic: 63% of them are less than 35 years old and 68% have a total household income of at least $\$60,000$ in the United States. Given the use of the medium and its demographic, it follows that the 'typical' Twitter user engages in immediate and informal communication (positive correlation for 'present' category), is concerned with the here and now (negative 'past'), and is young (youngsters have been found to be less concerned with the future - negative correlation for 'future' category [24]). Therefore, these three word categories (i.e., 'present', 'past', and 'future') are not expected to be informative as they reflect current shared norms in Twitter, while the remaining categories could be informative as follows. Based on previous work on social influence [2], [4], [5], [3], we posit that *listeners* (high $following$ count), *popular* users (high $followers$ count), and *highly-read* users (high $listed$ count[3]) are concerned with others rather than being self-focused (negative 'first' and positive 'second'). As opposed to those three user types, Twitter *stars* (high ratio $\frac{followers}{following}$) are expected to talk more about themselves than about others (positive 'first' and negative 'second'), and to tweet about how they spend their time (positive 'time'), rather than engaging in cognitive processes (negative 'cognitive'). In addition to being concerned with one-to-one communication, we expect *influentials* (high Klout/TrstRank scores) to express community engagement (negative 'first' and positive 'second' and 'third'), as this has been found to be necessary for social influence [2], [3]. Finally, there remain words expressing emotions. In the behavioral laboratory, research has found that a rumor will spread (and its initiator becomes influential) if it either engages people's emotions or is of quality. In both cases, emotions matter, but they matter differently, leading to two conjectures:

- The first conjecture is that emotions expressed in tweets make them spread. This conjecture is based on the research finding that, when rumors trigger strong emotions, people are far more likely to spread them. Chip Heath *et al.* have found that rumors "are selected and retained in the social environment in part based on their ability of tap emotions that are common to individuals" [11]. Based on this observation, we expect *influentials*' tweets to express both positive and negative emotions.
- The second conjecture is that emotions expressed in tweets reflect one's mood, and negative mood 'activates' cognitive strategies that lead to the production of quality tweets. This is based on experimental evidence that mood has a strong influence on argument quality [25], [30]. In experimental studies, participants "in a negative mood produced significantly higher quality and more persuasive arguments than did those in a happy mood. [...] sad mood increased the quality of arguments irrespective of the issues argued or the popularity of the position taken" [5]. However, "positive affect promotes a more creative, flexible, and internally focused processing style - hence greater argument originality - even though the overall quality and persuasiveness of arguments was higher in negative mood" [5]. Based on this observation, we thus expect *influentials*' tweets to express *negative* emotions (as well as have positive 'cognitive') .

V. RESULTS

To study the relationship between the ten linguistic categories (Table I) and our five user types (Table II), we compute the correlation coefficients of simple linear regressions between normalized values of the ten LIWC categories in Table I (predictors) and each of the following quantities: the logarithm of the number of following (for *listeners*), of followers (for *popular* users), of the ratio $\frac{followers}{following}$ (for *stars*), of the times a profile has been bookmarked in others' reading lists (for *highly-read* users), and of the influence scores (for *influentials*). We consider

[3]This is the number of times the user's account is listed in the 'reading list' of another user

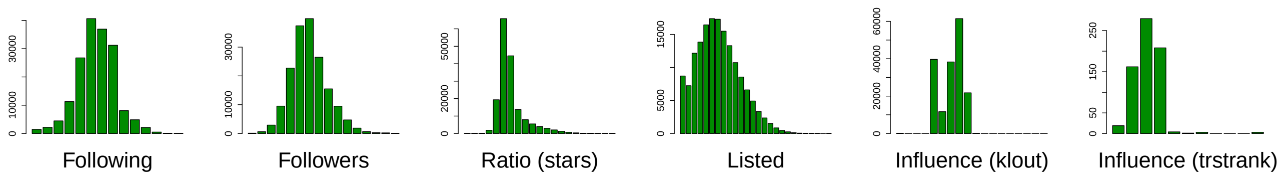


Figure 1. Frequency plots of the logarithms of the five quantities that define our five user types (i.e., following $\rightarrow$ *listeners*, followers $\rightarrow$ *popular users*, followers/following ratio $\rightarrow$ *stars*, listed $\rightarrow$ *highly-read users*, and Klout/TrstRank $\rightarrow$ *influentials*).

Coefficient	**Listeners** log(Following)	**Popular** log(Followers)	**Stars** log(Ratio)	**Highly-read** log(Listed)	**Influential** log(Klout)	**Influential** log(Trstrank)
r_{first}	**-0.16**(0.004)***	**-0.16**(0.04)***	0.00(0.004)	-0.08(0.004)***	0.07(0.01)***	-0.05(0.04)
r_{second}	**0.32**(0.004)***	**0.20**(0.04)***	**-0.11**(0.004)***	**0.11**(0.004)***	0.02(0.001)***	-0.02(0.04)
r_{third}	**-0.13**(0.004)***	-0.07(0.004)***	0.07(0.004)***	0.02(0.004)***	**0.10**(0.01)***	**0.10**(0.04)*
$r_{\text{cognitive}}$	0.08(0.004)***	-0.02(0.004)***	**-0.10**(0.004)***	-0.03(0.004)***	-0.02(0.01)***	**0.16**(0.04)***
r_{time}	**-0.23**(0.004)***	-0.11(0.004)***	**0.11**(0.004)***	-0.07(0.004)***	-0.05(0.004)***	-0.08(0.04)*
r_{past}	**-0.29**(0.004)***	**-0.25**(0.004)***	0.04(0.004)***	**-0.16**(0.004)***	0.08(0.001)***	0.01(0.04)
r_{present}	0.01(0.004)	-0.03(0.004)***	-0.03(0.004)***	0.01(0.004)**	0.07(0.001)***	-0.01(0.04)
r_{future}	-0.08(0.004)***	-0.07(0.004)***	0.02(0.004)**	-0.01(0.004)*	0.05(0.001)***	0.07(0.04).
r_{posemo}	**0.17**(0.004)***	**0.10**(0.004)***	-0.07(0.004)***	0.06(0.004)***	0.003(0.01)*	-0.07(0.04).
r_{negemo}	**-0.12**(0.004)***	-0.03(0.004)***	0.08(0.004)***	0.04(0.004)***	**0.10**(0.001)***	0.07(0.04).

Table III

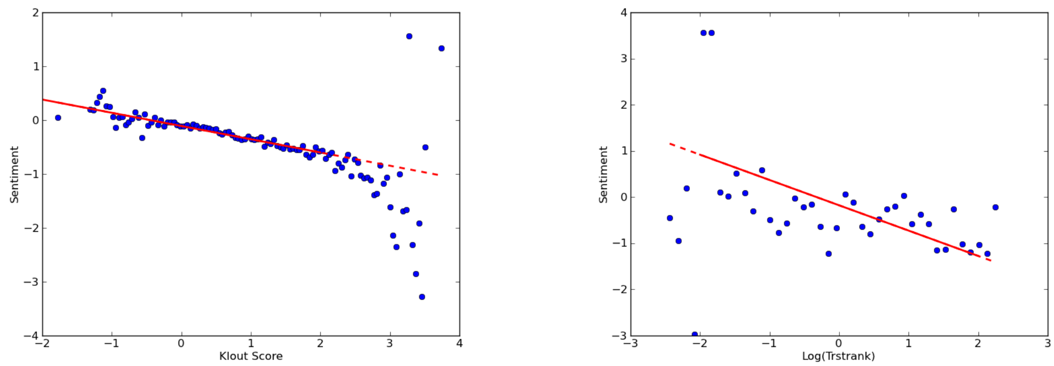
CORRELATION COEFFICIENTS r (AND STANDARD DEVIATIONS IN PARENTHESIS) OF SIMPLE LINEAR REGRESSIONS BETWEEN USE OF LANGUAGE IN TWEETS AND FIVE USER TYPES. HIGHLIGHTED ARE THOSE RESULTS THAT ARE BOTH STATISTICALLY SIGNIFICANT AND DISCUSSED IN THE PAPER BECAUSE OF INTEREST. p-VALUES ARE EXPRESSED WITH *'S: $p < 0.001$ $(***)$, $p < 0.01$ $(**)$, AND $p < 0.05$ $(*)$.

logarithms simply because original quantities show large variability: their logarithms show less of it (Figure 1); furthermore, considering them in linear regressions accounts for the violation of normality. Table III reports correlation coefficients and corresponding standard deviations. In general, a correlation coefficient within 2 standard errors is considered to be consistent with the data, and is thus *statistically significant*. For example, in the first column of Table III (*listeners*), we report a r_{second} coefficient of 0.32 with standard error of 0.004; in this case, we state that the data is consistent, with correlation in the range $[0.32 \pm 0.008] = [0.312, 0.328]$. We conclude that 0.32 is a statistically significant coefficient; since its p-value is < 0.001, we also mark it with three stars $***$ to indicate that the coefficient is highly significant. When an estimate is statistically significant, we are fairly sure that the estimate is stable and is not just an artefact of small sample size [7].

From the correlations that are statistically significant, two main insights emerge: 1) most of the results are as expected in that they are similar to those anticipated in the previous section; and 2) there exists a strong link between emotions and influence. For convenience, we collate the main insights in Table IV.

Confirmatory Results. From the correlation coefficients in Table III, we find that *listeners* and *popular* users are concerned with the here and now (r_{past} is -0.29 for listeners and -0.25 for popular). They are not concerned with themselves but with others (r_{second} is 0.32 and 0.20). By contrast, *stars* are self-centered (r_{second}=-0.11) and, as opposed to *listeners*, they tweet about how they spend their time (r_{time}=0.11) and, as opposed to (TrstRank) *influentials* (whose $r_{\text{cognitive}}$ is 0.16), do not explain the *whys* and *hows* in their tweets. This suggests that those who are popular beyond Twitter (as *stars* are likely to be) do not need to engage others and can be focused on themselves. For the two remaining user types, we find that *highly-read* users are concerned with others (r_{second}=0.11); instead, *influentials* express a sense of community with their tweets (r_{third}=0.10 and this is second highest correlation coefficient for the two influence scores, with only $r_{\text{cognitive}} = 0.16$ being higher). In summary, these results are indeed aligned with the hypothesis we postulated in the previous section (and we have now determined the extent to which they are so): listeners, popular users and highly-read users are concerned with one-to-one engagement, influentials create a sense of community, while stars are self-centered.

Central role of Emotions. The role of emotions on influence has been largely studied in the laboratory (as we have already mentioned in the previous section); it is now striking to see that similar findings hold in Twitter too. From Table III, we learn that *popular* users predominantly use positive emotions (r_{posemo}=0.10), while negative emotions



(a) Klout

(b) TrstRank

Figure 2. The relationship between profile sentiment and profile influence (two influence scores considered).

User Types	Findings
Listener	Concerned with one-to-one and with the here and now Express positive emotions and avoid negative ones
Popular	Concerned with one-to-one and with the here and now Express positive emotions
Star	Self-centered; express how they spend their time
Highly-read	Concerned with one-to-one and with the here and now
Influential	Express sense of community Express negative emotions

Table IV
SUMMARY OF OUR FINDINGS FOR THE FIVE TYPES OF USER.

do not characterized them; Klout *influentials* do the opposite instead: they express negative emotions, while positive ones do not characterize them (r_{negemo}=0.10). Again, Table IV collates the main insights for convenience.

As a final investigation into the correlation between sentiment and influence, we have derived a sentiment metric that decreases the dependency of language and dictionary, by discounting negative emotions from positive ones, in a way similar to what Kramer did [16]:

$$Sentiment_i = \frac{p_i - \mu_p}{\sigma_p} - \frac{n_i - \mu_n}{\sigma_n} \quad (2)$$

where p_i (n_i) is the fraction of positive (negative) words for user i; μ_p (μ_n) is the fraction of positive (negative) words, averaged across all users; and σ_p (σ_n) is the corresponding standard deviation. We normalize using means and standard deviations to account for the unbalanced distribution of positive and negative words of the English language. Critics might well say that keyword matching does not necessarily produce sufficiently accurate sentiment classifications to justify its use. To see whether this is true, we have implemented the Maximum Entropy classifier, which is a state-of-the art method for classifying sentiment of single tweets, and compared it to keyword matching. We found that Maximum Entropy better classify single tweets (it has higher recall), but the two algorithms classify entire profiles in a very similar way [26]. Therefore, simply counting keywords produces sufficiently high accuracy rates to justify its use at profile level.

Figure 2 plots this sentiment metric as a function of influence (Klout and Trstrank) scores and shows a strong negative correlation between the two quantities. On the range $x \in [-2, 2]$, the linear fits have coefficients as high as -0.924 (Klout) and -0.599 (TrstRank). These results suggest that Twitter users are influenced by those who express negative emotions. Two explanations might be put forward. The first is that influentials not only create a sense of community around them, but also create a sense of intimacy with their audience using emotion words. This explanation alone does not justify the neat prevalence of negative emotion words over positive ones among influentials (especially because rapidly-fading tweets contains significantly more words expressing negative emotion [34]). We thus provide a second explanation: individuals reflect their mood in the tweets they produce and, according to the literature of social influence, individuals in a negative mood employ specific cognitive processing styles that allow them to produce influential ideas. This provides, for the first time, empirical and quantitative evidence that negative mood is associated with influence, not only in the behavioral laboratory but also in Twitter.

VI. Conclusion

We have studied one specific aspect that mediates interactions between users - their use of language - and have found that it is linked to social influence. We have found that language, with its vocabulary and prescribed ways of communicating, is a symbolic resource that can be used on its own to influence others on Twitter. Expressing a sense of community correlates with influence, as conventional wisdom holds, and expressing negative emotions reflects one's mood, which in turn impacts one's influence. These findings point to important theoretical and practical implications:

Theoretical Implications. Twitter is a distal communication modality (distal in the sense that users are separated in space and time) and was originally designed not as a social-networking tool but as a broadcasting platform of publicly available news and opinions. Yet, insights from our linguistic analysis suggest that the medium partly resembles proximal communication between individuals embedded in offline social networks: influence is not gained spontaneously but partly depends on linguistic qualities that reflect one's personality and mood.

Practical Implications. In addition to user activity and user topics, linguistic features can be used to identify influentials. This is good news for social media marketers willing to promote their campaigns and for policy makers willing to promote social change - by reaching influentials, they will be able to trigger successful campaigns and/or promote real social change.

Based on these promising results, in the future, more work will likely go into understanding the relationship between psychological/cognitive processes and social influence, though whether to sell the latest electronic gadget or to promote social change may be another question.

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