Predicting Personality with Social Behavior

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***Abstract*—In this paper, we examine to which degree behavioral measures can be used to predict personality. Personality is one factor that dictates people's propensity to trust and their relationships with others. In previous work, we have shown that personality can be predicted relatively accurately by analyzing social media profiles. We demonstrated this using public data from facebook profiles and text from Twitter streams. As social situations are crucial in the formation of one's personality, one's social behavior could be a strong indicator of her personality. Given most users of social media sites typically have a large number of friends and followers, considering only these aspects may not provide an accurate picture of personality. To overcome this problem, we develop a set of measures based on one's behavior towards her friends and followers. We introduce a number of measures that are based on the intensity and number of social interactions one has with friends along a number of dimensions such as reciprocity and priority. We analyze these features along with a set of features based on the textual analysis of the messages sent by the users. We show that behavioral features are very useful in determining personality and perform as well as textual features.**

I. Introduction

Personality is an important trait that moderates people's behavior and interactions with one another. In essence, personal tendencies are shaped further through social interactions where individuals in a social network act similarly, sometimes referred to as normative (or normal) behavior. Furthermore, research has shown that distinctive characteristics of one's personality are more likely to manifest themselves in situations that satisfy individuals basic psychological needs [1]. These needs are summarized as relatedness to others, competence, and autonomy, which social networking sites like Twitter are well positioned to satisfy. As opposed to sites that invite more adversarial discussion like political blogs, sites like Twitter allow one to create their own circle and communicate only with those in their circle. Personality tests like the Big Five capture both these normative and distinctive characteristics of one's personality. Our hypothesis is that social behavior in these sites is a good indicator of one's personality. This is due to two factors. First, there is ample data about the normative behavior of one's social circle which is given by the behavior of one's friends and followers. Secondly, Twitter also provides an environment where individuals get to talk freely about topics in which they find themselves knowledgeable which allows them to display their distinctive personality features.

Our previous work has shown that people reveal their personality traits through their use of social media in the case of Facebook [2] and on Twitter [3], [4], where personality traits can be predicted with relatively high accuracy by analyzing public data that people share online. In the latter case, a combination of text analysis and structural characteristics were used to predict personality traits of subjects. In this paper, we look at whether or not using behavioral features alone are enough to predict personality. We introduce measures that capture information about users' relationships and Twitter use, analyze their correlations with personality data, and compare the accuracy of personality prediction algorithms over behavioral data to that achievable with text analysis. We find statistically equivalent performance, suggesting behavior is just as useful in predicting personality as automated text analysis is. Our results provide an important insight that could be especially important analyzing behavior in social media sites. When studying behavior in these sites, one has to take into consideration the moderating effects of the external situation factors. Situations with high uncertainty and risk may lead to behavior where one is expected to behave very similar to the group, the so called herd effect. In other cases, one's behavior may be more indicative of the distinctive aspects of one's personality which might be useful for developing methods to analyze communities and their composition.

II. Related Work

There are two widely accepted personality models: Myers-Briggs, a four factor model, and the Big Five, a five factor model. We chose the latter as it was most convenient to administer the corresponding test to our subjects. The "Big Five" model of personality dimensions has emerged as one of the most well-researched and well-regarded measures of personality structure in recent years. The model's five domains of personality, Openness, Conscientiousness, extroversion, Agreeableness, and Neuroticism, were conceived by Tupes and Christal [5] as the fundamental traits that emerged from analyses of previous personality tests [6]. McCrae & Costa [7] and John [8] continued five-factor model research and consistently found generality across age, gender, and cultural lines [6]. Additional research has proved that different tests, languages, and methods of analysis do not alter the model's validity [6], [9], [8], [10]. Such extensive research has led to many psychologists to accept the Big Five as the current

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definitive model of personality [11], [12]. It should be noted that the model's dependence on trait terms indicates that the Big Five traits are based on a "lexical approach" to personality measurement [11], [13], [9], [14]. The Big Five traits are characterized by the following:

- Openness to Experience: curious, intelligent, imaginative. High scorers tend to be artistic and sophisticated in taste and appreciate diverse views, ideas, and experiences.
- Conscientiousness: responsible, organized, persevering. Conscientious individuals are extremely reliable and tend to be high achievers, hard workers, and planners.
- Extroversion: outgoing, amicable, assertive. Friendly and energetic, extroverts draw inspiration from social situations.
- Agreeableness: cooperative, helpful, nurturing. People who score high in agreeableness are peace-keepers who are generally optimistic and trusting of others.
- Neuroticism: anxious, insecure, sensitive. Neurotics are moody, tense, and easily tipped into experiencing negative emotions.

Even though personality traits are determinants of behaviors, they are latent constructs. A person's behavior is not simply a function of their personality traits: an aggressive person will behave aggressively in certain situations. The situational cues lead to activation of personality traits which then lead to a behavioral expression [15]. The impact of personality on job performance has been studied a great deal as jobs provide a rich set of distinctive situational cues that can be studied [16]. Tett and Burnett [17] studied cues provided by specific jobs at both individual, social and organizational levels. The social level is of particular interest to this work as the studied medium allows individuals to engage in social interactions. Friendship ties favor reciprocal behavior, but people who have access to a variety of ties tend to have access to more diverse information [18]. Individuals with mostly friendship ties tend to favor cohesive networks, which has been associated with agreeableness. Information propagation can be viewed a validation of another's viewpoint, which is shown to be correlated with openness [17]. Extraversion signals dominance (control over others) and sociability, which is shown to be a predictor of performance in jobs requiring these skills (i.e. managers and sales).

Research has studied the impact of personality on social relationships and in particular network position. Burt et. al. [19] show that personality correlates with network position. People who connect nodes who otherwise would not be connected are entrepreneurs, they tend to have a mix of ties. Their personality differs strongly from those who tend to favor stability in the network and hence have strongly embedded ties, which suggests the networks of friends is also important. In our previous work [20], we have shown that we can distinguish between friendship ties and ties used for formal information exchange. We expand on some of these behavioral features in this study, but adapt them to individuals and their social network.

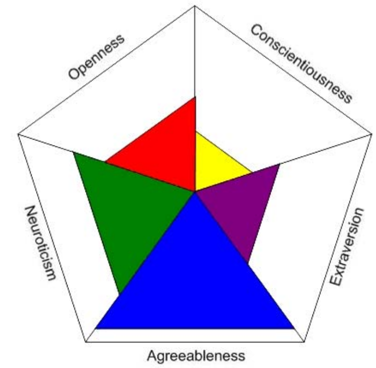

Fig. 1. A person has scores for each of the five personality factors. Together, the five factors represent an individual's personality.

Klein et. al. [21] study network centrality in various types of networks. In friendship networks, people tend to look for comfort and companionship. Advice networks tend to provide expert information, similar to our arm's length ties, generally modeled by information propagation patterns. Adversarial networks are formed by those individuals who are avoided by others because they provide little value to the network. Klein's work shows that neuroticism and openness are negatively correlated with friendship centrality. Openness is positively correlated with adversarial centrality, suggesting that open individuals are not well liked by the others. Extraversion is not a predictor of friendship personality, but positively correlated with adversarial centrality. Asendorpf et. al. [22] show that personality impacts relationships between people: social and extraverted individuals spend more time with others, creating larger social circles. Agreeableness is predicted by low conflict with peers. While conscientiousness does not impact the longevity of the relationships, it impacts the contact frequency.

III. Behavior Features

To understand personality within the scope of social behavior, we analyze various behaviors of individuals in their social network. We consider actions in the following main groups:

- Nextwork Bandwidth (NET): the amount of overall activity and size of social network, the distribution of activity over time (uniform or bursty), how long they have been using the online system,
- Message Content (MSG): the type of messages they send, whether they contain URLs or other types of links, whether they are forwarded, etc.,
- Pair Behavior (PAIR): their behavior towards their friends and followers, both the average and the standard deviation of measures of various actions across different friends/followers,
- Reciprocity of actions (REC): to which degree their actions are reciprocated by their friends,
- Informativeness (INF): How informative are various behavior features across all the friends, are there specific

types of actions uniform across friends or favor a small group over the others?
- Homophily (HOM): All the previous features computed for the person's friends to understand her social circle.

The features are chosen to gain insight on various aspects of personality. The NET and MSG features show the behavior of the person in public, towards all friends. The PAIR features are meant to capture actions that indicate decreasing social distance with respect to specific individuals. It is computed with respect to all the friends that they correspond with. For example, having close friends with long conversations indicates a decrease in social distance. INF features capture the social network of the individual, they are computed for a number of PAIR features. Similar to previous studies on network location and cohesiveness of the ties, INF features capture if the person is social towards some or all friends. The least informative case for a person would be if she acts the same towards all the friends. For example, if she has long conversations with all friends, then the informativeness of this feature would be low. On the other hand, the most informative case would be if she had only one friend out of a large number she has long conversations with. In that case, the conversation length determines who the friend is easily and is an informative feature. This type of feature is especially useful for capturing distinctiveness of the behavior along a specific axis.

The final set of features HOM comes from the well-known social science phenomenon of homophily: people tend to be friends with people who are similar to themselves. Hence, we can also examine the behavior features of their friends to understand a person. Furthermore, these features allow us to understand whether the friends of a person are homogeneous or heterogeneous, supporting the claims that structural holes are entrepreneurial people who connect diverse sets of individuals [19]. For this set, we compute the average of all the previous features for the friends of the person. We have introduced a number of the pair features in previous work to understand the relationships between pairs of individuals. We have shown that these features can be used to distinguish between affective relationships and information exchange relationship in the scope of Twitter messages. However, the remaining features are novel and none of the features shown here have been applied to personality prediction.

A. Computation

The details of the user set we consider are given in Section IV. To compute our features, we find all the messages sent by a set of users from Twitter. These messages are a mix of broadcast messages, meant for anyone who is following the user and directed messages, meant for a specific user but visible to all the followers. Based on this data set, we compute the above set of features. In this section, we describe them in more detail.

Many features are based on the reciprocity of a specific type of action by A towards B, and the same action by B towards A. For this, we use the entropy measure. We will denote messages from A to B with $A \rightarrow B$. Suppose x_1 is the quantity describing the amount $A \rightarrow B$, and x_2 is the quantity for $B \rightarrow A$. Now, we compute entropy of x_1, x_2 as follows given $p = \frac{x_1}{x_1+x_2}$:

$$H(x_1, x_2) = -p \log p - (1-p) \log(1-p)$$

Entropy is the highest when $x_1 = x_2$ which is the highest level of reciprocity or balance between two measures.

Feature	Description
`Fr`	#Friends
`Fo`	#Followers
`Msg`	#Messages posted
`Fav`	#Messages favorited
`Days`	#Days the user has been on twitter
`Time`	Mean spacing between tweets
`Rtw`	Fraction of tweets that are retweets
`Dir`	Fraction of tweets that are directed
`URL`	Mean number URLs in a tweet
`Hash`	Mean number of hashtags in a tweet
`Men`	Mean number of mentions in a tweet
`Len`	Mean text length

Fig. 2. Network Bandwidth and Message Content Features. Note that for all features computing mean, there is a corresponding feature computing the standard deviation, for example ρTime denotes the standard deviation of time.

a) Pairwise Features: The network bandwidth features capture the behavior of the person in front of their whole network, including broadcast messages. However, we also would like to analyze their behavior with respect to a specific friend and follower. In particular, they can exchange direct messages with each other or they can forward messages from a friend or follower to their network. These two behaviors are slightly different. Propagation or being propagated generally represents one's reputation in the network. However, back and forth messages between two individuals typically correspond to more intimate conversations. In our previous work, we show that relationships containing mostly conversations are typically of an intimate nature such as friendship, while propagation based relationships are based on transfer of ideas [20]. If propagations are not reciprocal, the source of propagated information is likely not a social tie, but an acquaintance or possibly not even known the propagating party.

To analyze these types of features, we consider two types of behavior traces. A conversation is a sequence of directed messages $m_1, \ldots, m_n$ where each message is either from A to B or from B to A. We consider all messages between A and B, and compute the average inter-message time τ between messages. We then find a sequence of message $m_1, \ldots, m_n$ such that the time between each message is less than $c * \tau$ for some smoothing factor c. Note that for conversations to exist one message each from A and B and 3 messages total. We cap τ at 2 weeks. For a given user A, we compute conversations for each of her friends separately and compute features based on the conversations: mean/max/min number of messages in conversations, the τ value, number of conversations, balance of messages in the conversations (entropy of number of messages $A \rightarrow B$ and $B \rightarrow A$) and a conversation total called `ConvT` that sums over all conversations, the number of messages in the conversation times the balance. Note that Twitter now supports conversations that can be traced by the replies, however this feature is not available in our studied set. As a result, we compute conversations algorithmically.

Another type of feature computes the relative importance given to friends. Delay computes average the number of messages a person is delayed, i.e. how many other messages that arrived after this message are answered before answering this person's message. Priority computes how many times a person is prioritized over someone else's message. Delay and priority show to which degree one's behavior towards their circle is homogeneous. We also compute features based on the number, reciprocity and timing of all messages (not just those that constitute a conversation) between the two users.

Propagation is computed by finding pairs of messages m_1, m_2: m_1 from A to B, and m_2 from B to someone other than A or broadcast. The idea is that B propagates a message from A to others. Similar to conversations, we compute propagation algorithmically based on the timing of messages. We do not check true propagation in the form retweets as propagation may be in message content implicitly or explicitly. We find a maximum match between messages $A \rightarrow B$ and messages from B to anyone else satisfying the causality constraint. Our prior work showed that our method has significant correlation with true propagation behavior [23]. Based on propagations of B from A, we compute the number of propagations, worthiness of A (the number of messages of A that are propagated) and attention to A (the number of propagations of B that are from A). We also compute the same for B as well as the propagation reciprocity of A and B. The degree similarity is given the entropy of the number of friends A and B have.

For each user, we find the mean and standard deviation of these features across all the people they converse with, propagate to and from as shown in Figure 3 (note that we show only features based on mean for brevity).

b) Distribution of behavior across friends (KL): In addition to the behavior features that look mainly at mean and standard deviation of features towards all friends, we also look at to which degree friends are distinguished from each other (i.e. INF). We first look at distribution $X = x_1, \ldots, x_k$ of the behavior of A across all her friends for a specific feature and compare how different this distribution is from uniform distribution. The most non-uniform, i.e. informative value is when one friend has a value of 1, and all the others have a value of 0 for this feature. To compute the divergence from uniform, we use the Kullback-Leibler measure from information theory. Given X is normalized to add up to 1, we compute

$$KL(X \| U) = \sum_{i=1}^{k} (x_i * \ln(\epsilon + \frac{x_i}{1/k}))$$

Feature	Description
`PropbyA`	#users that A propagates
`PropfrA`	#users that propagate from A
`ConvU`	#users that converse with user
`PropU`	#users that propagate from the user
`Resp`	mean response time $A \rightarrow B$
`RespH`	balance of response time $A \rightarrow B$, $B \rightarrow A$
`Prop#`	mean #propagations $A \rightarrow B \rightarrow X$
`Attn`	mean attention to A
`Worth`	mean worthiness of A
`PropH`	mean propagation reciprocation
`Conv#`	mean number of conversations
`ConvMsg`	mean number of messages per conversation
`ConvTau`	mean tau in conversations
`ConvH`	mean balance in conversations
`ConvT`	mean combined conversation value
`Del`	mean delay
`Pri`	mean priority
`DelH`	mean delay reciprocity
`PriH`	mean priority reciprocity
`Assor`	mean degree similarity of A with friends
`BalIn`	mean balance of messages A,B received from anyone
`BalP`	mean balance of msgs $A \rightarrow B$, $B \rightarrow A$
`#PMsg`	mean #messages $A \rightarrow B$

Fig. 3. Pairwise features for a user A to any of the people she communicates directly with.

by comparing the distribution X of values to the uniform distribution. This value is lowest when X is uniform and hence least informative (note, we use ϵ to make sure the function is always computable). Higher values of KL means that a high values for X are very informative, they tell us who the friends might be. We compute the KL divergence of all features above that vary across friends. Our aim is to find to which degree the behavior of the individual differs from friend to friend, especially in terms of timing and number of messages.

c) Tell me who your friends are (FF): Based on hypothesis that the above features are predictive of one's personality, we then test the homophily hypothesis well-known in social networks [24]. The homophily hypothesis that birds of a feather flock together means that one's friends are likely to exhibit similar behavior patterns. Research shows that psychological well adjusted individuals exhibit normative behavior, i.e. behavior that is in congruence with their social group [1]. To compute this normative behavior patterns, we simply compute the mean of all the above features for each friend B of user A. These friend features are added to the main set of features. We will use the notation `STD-f`, `KL-f` and `FF-f` to denote the new features based on an existing feature `f`. `STD` is the standard deviation of values instead of mean, `KL` is the Kullback-Leibler distance. Both, `STD` and `KL` are computed for the user A. `FF` on the other computes the same feature for A's friends towards their friends.

IV. Setup

A. The Big Five Personality Test

We use a 44-question version of the Big Five inventory [25] in this work. The test begins with the statement "I see myself as someone who..." and then presents the subject with 44 phrases to complete the sentence. The subject rates each question on a 1 to 5 scale, where 1 indicates "Strongly Disagree" and 5 indicates "Strongly Agree". Example phrases include:

- ...Is reserved
- ...Is helpful and unselfish with others
- ...Can be somewhat careless
- ...Is relaxed, handles stress well

Each personality trait is associated with a set of statements, and the score for a trait is given as the average of the subject's ratings on the associated questions.

B. Subjects and Data

For our study, we have a set of 71 users who have taken the personality test. To this set, we add all the friends and followers of the survey takers and collect all the public tweets of the given set of users (up to 3200 allowed by Twitter). This includes public messages that are directed to a specific person but still public to all. Messages can contain URLs to other pages, they can contain mention other Twitter users and they can mention specific topics by means of hashtags which are topic handles. For the behavioral features, we only process messages for these markers, but do not interpret the content in our feature set. The tweets also contain additional meta-data about the users. In our analysis, we remove all users with fewer than 3 tweets total. This leaves us with a total of 21,525 users, 60 of whom filled out the personality survey. We also construct pairs of individuals from this dataset by selecting pairs who have sent each other at least one directed message. This gives us 279,753 unique pairs of individuals for analysis. Based on this information, we compute the features described in the previous section.

V. Analysis

In our initial analysis, we first find which of the above features are predictive of different personality traits. Based on our survey, for each user and each personality trait, we have a score. Each personality trait t_i is then a vector containing the values for this trait for all the users in our data set. For the same users, we compute the above behavioral features, get X. Each row in X is the list of behavioral features for a user in our data set.

We first compute for each personality trait t_i, the best predictors of this trait based on behavior. To accomplish this, we use Forward subset selection based regression (FSSreg). FSSreg performs a regression using an input matrix X and target vector y and results in weights w of the predictor $X^T w$. The weights w are obtained using a greedy forward stepwise regression to minimize the leave-one-out cross validation error. Specifically, suppose that k features from X have been

TABLE I
Correlations between features and personality traits.
Significant values ($p < 0.05$) are shown in bold.

	E	A	C	N	O
STD-Fo	-0.077	-0.136	-0.013	**0.302**	-0.072
Days	-0.063	0.027	0.033	**-0.273**	**-0.263**
STD-Time	-0.047	-0.019	0.004	0.011	**-0.348**
Hash	0.220	**0.259**	-0.060	-0.096	**0.315**
STD-Hash	0.175	**0.310**	-0.020	-0.086	**0.256**
Len	**0.302**	0.152	-0.012	-0.069	**0.293**
STD-Len	-0.239	-0.093	-0.215	**0.315**	-0.248
Prop#	**-0.278**	0.011	-0.082	0.073	-0.111
STD-Worth	0.072	-0.156	**-0.260**	0.100	-0.017
STD-ConvMsg	**-0.291**	0.031	-0.122	0.026	-0.191
KL-ConvTau	0.019	0.189	**-0.257**	0.049	-0.058
KL-PMsg	-0.132	0.162	**-0.304**	0.082	-0.074
KL-PriH	-0.100	0.006	**-0.252**	0.148	-0.112
KL-RespH	-0.066	-0.144	**-0.340**	0.190	-0.107
ConvTau	-0.143	-0.008	**-0.254**	0.113	-0.143
#PMsg	**-0.285**	-0.034	-0.118	0.064	-0.203
ConvMsgH	-0.042	0.139	**-0.301**	0.049	-0.063
DelH	-0.104	0.128	**-0.283**	0.028	-0.068
Pri	-0.102	0.094	**-0.283**	0.019	-0.061
BalP	-0.042	0.141	**-0.305**	0.046	-0.061
InDegH	-0.133	0.119	**-0.252**	0.131	-0.148
RespH	-0.143	**0.281**	-0.131	-0.078	-0.125
STD-ConvTau	0.073	**0.289**	-0.143	-0.039	-0.063
STD-PMsg	**-0.258**	-0.012	-0.165	0.102	-0.110
FF-Msg	-0.038	0.039	**-0.302**	0.111	-0.065
FF-Fav	0.011	**-0.285**	-0.227	**0.301**	-0.165
FF-Rtw	-0.007	0.054	**-0.299**	0.030	0.067
FF-Dir	-0.071	-0.083	**-0.258**	0.099	-0.096
FF-Msg	0.046	-0.031	**-0.265**	0.158	0.033
FF-URL	-0.034	0.081	**-0.260**	0.041	-0.013
FF -Hash	0.074	0.106	**-0.264**	0.016	0.239
FF-STD-Hash	0.032	0.103	**-0.267**	0.011	0.161
FF-Men	-0.013	-0.024	**-0.289**	0.100	-0.024
FF-STD-Men	0.002	0.040	**-0.263**	0.083	-0.015
FF-Len	0.015	0.050	**-0.315**	0.063	0.105
FF-ConvU	0.098	0.026	**-0.273**	0.111	0.052
FF-Resp	0.101	**0.256**	-0.032	-0.137	0.144
FF-Prop#	0.046	**-0.290**	-0.150	0.183	0.081
FF-Std-Attn	0.107	-0.051	**-0.312**	0.060	0.156
FF-Worth	0.062	-0.020	**-0.305**	0.143	0.150
FF-Std-Worth	-0.037	-0.212	**-0.280**	0.250	0.060
FF-PropH	0.080	-0.022	**-0.336**	0.127	0.052
FF-Conv#	-0.117	0.034	**-0.293**	0.100	-0.039
FF-STD-ConvTau	-0.042	-0.026	**-0.266**	0.033	0.124
FF-STD-ConvH	-0.070	-0.021	**-0.282**	0.096	0.188
FF-STD-ConvT	-0.118	-0.214	**-0.286**	0.188	0.024
FF-KL-ConvTau	-0.006	-0.085	**-0.344**	0.113	0.003
FF-KL-PMsg	0.006	0.066	**-0.267**	0.013	-0.045
FF-KL-Resp	-0.083	-0.021	**-0.313**	0.086	-0.041
FF-KL-PropH	0.118	-0.008	**-0.270**	0.098	0.084
FF-KL-Assor	0.048	-0.015	**-0.286**	0.077	0.057
FF -PropH	-0.010	-0.059	**-0.259**	0.162	0.013
FF -Assor	0.019	0.010	**-0.311**	0.111	0.053
FF-ConvMsgH	0.005	0.098	**-0.261**	0.043	0.035
FF-DelH	-0.038	0.059	**-0.270**	0.026	-0.022
FF -BalP	0.005	0.099	**-0.262**	0.042	0.035
FF-RespH	-0.049	0.058	**-0.259**	0.019	-0.073
FF-STD-ConvTau	0.043	0.014	**-0.296**	0.051	0.091
FF-STD-PropH	0.047	-0.056	**-0.316**	0.167	0.051
FF-STD-Assor	0.034	-0.044	**-0.330**	0.149	0.059
FF-ConvMsgH	-0.052	0.015	**-0.263**	0.083	-0.007
FF-STD-Pri	-0.012	-0.001	**-0.276**	0.144	0.060
FF-STD-BalP	-0.051	0.019	**-0.266**	0.079	-0.007
FF-STD-InDegH	0.002	0.083	**-0.259**	0.014	0.024

Extroversion	
10	Len
-4	Prop#
2.8	STD-Attn

Agreeableness	
-3.5	FF-STD-Attn
2.9	Hash
2.46	RespH
2.44	FF-Resp

Openness	
-3.57	STD-Time
-2.26	KL-PropH
2.14	FF-Resp

Conscientiousness	
-3.5	FF-Assor
3.07	FF-Time
-2.99	KL-#PMsg
-2.77	KL-RespH

Neuroticism	
3.00	STD-Len
-7.63	Days
-4.45	FF-Rtw
3.44	FF-STD-Prop#
3.03	STD-Resp
-2.19	Attn
1.42	FF-Fav

Fig. 4. The features that are most predictive of the specific personality traits based on the FSS analysis.

selected. We select the next feature to minimize the LOO-CV error assuming the first k features are selected. If the LOO-CV error decreases with the $k + 1$th feature, then the process continues. Otherwise it stops and we output the sparse regression vector w using only the k selected features. We apply FSSreg to each trait independently. The results of the FSS analysis are given in Figure 4. Note that due to the nature of FSS, it produces a sparse set of features. Hence, only a few features are found for each trait among the large set we have tested. With FSS, we are able to find the most significant linear combination for predicting a given trait, taking into account that some features can be highly correlated with each other. We also compute the pairwise Pearson correlation coefficients between all the features and personality traits. These results are given in Table IV-B with significant values ($p < 0.05$) bolded.

First, we note that neuroticism is best predicted by standard deviation of text length and response time. Both are positively correlated, in other words, higher standard deviation signals higher neuroticism. One can speculate that this implies more emotionally charged behavior. Similarly, neuroticism is negatively correlated with propagation. Not being propagated, having friends who do not propagate are indicators of this trait. This could be due to the nature of the messages sent by the user, but it is also interesting to note that the general behavior of the friends is also an indicator. Not being on Twitter for a long time is also a very strong indicator, which would support the erratic behavior patterns implied by the other features.

Extraversion is best predicted by text length, extraverted individuals tend to write long messages. However, they are not propagated by others frequently and the propagations seem to vary across friends. One can speculate that while extraverted individuals write long messages, they are meant to express self and initiate exchange with others. Propagations are on the other hand are for informive messages.

Agreeableness tend to be positively correlated with mentioning of topics, balanced relationships with friends in terms of response times and having friends with long response times. Agreeableness in other words imply accommodation of friends and replying to them in their timeline. The use of hashtags for topics may imply participation in discussion with others and also adherence to the norms of the media site. Furthermore, this trait tends to favor friends who have similar propagation characteristics.

The top features for openness seem to signal a diversity of experience for the individual across the people they communicate with. The features indicate a low variance of timing between tweets and almost uniform propagation behavior from friends.

Whenever a KL feature is negatively correlated, this implies a normative behavior. In conscientiousness, we see this both for the number of messages to specific friends and the reciprocity of response times. This seems to support the hypothesis that conscientious people are more organized and reliable. The behavior is uniform towards the friends, but friends themselves do not have the same property. In fact, the friends appear to have low assortativity, having friends that unlike themselves in terms of their degree.

Overall, the timing between messages, text length and propagations appear to be the most informative features for personality. Similarly, studying friends' behavior in general provides with many useful features for understanding the person's personality from a normative perspective.

Studying each behavior individually. We also check for each behavioral feature, the personality traits that best represent that feature. In our previous tests, we found a linear combination of behavioral features that best model each trait. Now, for each behavioral feature, we find the personality traits that best represent that feature, using the FSS function again. For all behavioral features (except for two), we find a single trait and these mappings mirror the ones shown in Figure 4 in reverse direction. In addition, we find that `Fr, Fo` are best represented by extraversion, as these show how socially active the person is. But, none of the features that signal close relationships map to extraversion. `Resp, PropU, Hash` are best represented by openness, as well as features that indicate that the friends have balanced relationships and are propagated by others. It seems users who use the site for propagating information and discussing specific topics of general interest have the openness trait. In contrast with all the other traits, a large number of features predict conscientiousness, but with a negative correlation. In particular, a large majority of FF features map to conscientiousness. Hence, having friends with low KL (uniform treatment of their friends), low STD (steady behavior), low retweet and short messages are predictive. One might speculate that these features signal having friends that use the site mostly for personal relationships and messages, instead of promoting themselves.

VI. Prediction

To predict the score of a given personality feature, we performed a regression analysis in Weka [26]. We used two regression algorithms: Gaussian Process and ZeroR, each with

TABLE II
NORMALIZED MEAN ABSOLUTE ERROR OF THE ZEROR AND GAUSSIANPROCESS ALGORITHMS FOR EACH PERSONALITY TRAIT AND DATASET.

Personality Trait	MAE	Dataset	Algorithm
Conscientiousness	0.146	F2	ZeroR
Conscientiousness	0.140	F2	GaussianProcesses
Conscientiousness	0.146	F2P	ZeroR
Conscientiousness	0.136	F2P	GaussianProcesses
Conscientiousness	0.146	F3	ZeroR
Conscientiousness	0.138	F3	GaussianProcesses
Conscientiousness	0.146	L	ZeroR
Conscientiousness	0.146	L	GaussianProcesses
Extraversion	0.163	F2	ZeroR
Extraversion	0.164	F2	GaussianProcesses
Extraversion	0.163	F2P	ZeroR
Extraversion	0.172	F2P	GaussianProcesses
Extraversion	0.163	F3	ZeroR
Extraversion	0.167	F3	GaussianProcesses
Extraversion	0.163	L	ZeroR
Extraversion	0.167	L	GaussianProcesses
Neuroticism	0.189	F2	ZeroR
Neuroticism	0.194	F2	GaussianProcesses
Neuroticism	0.189	F2P	ZeroR
Neuroticism	0.197	F2P	GaussianProcesses
Neuroticism	0.189	F3	ZeroR
Neuroticism	0.195	F3	GaussianProcesses
Neuroticism	0.189	L	ZeroR
Neuroticism	0.190	L	GaussianProcesses
Openness	0.124	F2	ZeroR
Openness	0.126	F2	GaussianProcesses
Openness	0.124	F2P	ZeroR
Openness	0.124	F2P	GaussianProcesses
Openness	0.124	F3	ZeroR
Openness	0.125	F3	GaussianProcesses
Openness	0.124	L	ZeroR
Openness	0.124	L	GaussianProcesses
Agreeableness	0.118	F2	ZeroR
Agreeableness	0.118	F2	GaussianProcesses
Agreeableness	0.118	F2P	ZeroR
Agreeableness	0.124	F2P	GaussianProcesses
Agreeableness	0.118	F3	ZeroR
Agreeableness	0.118	F3	GaussianProcesses
Agreeableness	0.118	L	ZeroR
Agreeableness	0.123	L	GaussianProcesses

a 10-fold cross-validation with 10 iterations. Two algorithms had similar performance over the personality features. Results are shown in table V. We used three sets of the features described above:

- F2: The full set of features mentioned above
- F2P: All features from F2 except those based on standard deviation and features of friends.
- F3: A subset of F2, based on the features returned by the FSS analysis for any trait.

We also ran prediction using features obtained by analyzing the text of users' tweets with LIWC [27], the Linguistic Inquiry and Word Count. This tool is a psycholinguistic analysis tool that processes a text document and outputs the percentage of words that match pre-defined categories. These include features like "anxiety words" (e.g. worry, nervous), "biological process words" (e.g. eat, sick), "happy words", and so on. It also counts words based on parts of speech, the type of punctuation used, and average word length.

Although the text people use is clearly a behavior, the type of features detected by LIWC are quite different than those described earlier in this paper. Furthermore, they were used heavily in our previous work on predicting personality on Twitter [3]. Predictions made using the LIWC features are marked as dataset "L".

As seen in table V, all datasets have similar prediction performance for each feature. Mean Absolute Error indicates reasonably good performance on predicting agreeableness and openness, with error rates around 11-12%. Neuroticism is much more difficult to predict, with error around 18-19%. Extraversion and conscientiousness fall in the middle, with error rates between 14% and 16%. Note that for all personality traits, the behavioral features we developed perform as well as text-based prediction using the features from LIWC.

VII. CONCLUSIONS

In this paper, we presented a series of measures for understanding behavior on Twitter, showed correlations between those measures and personality traits, and demonstrated that personality prediction using behavioral features was equivalently successful to prediction using text features. In particular, we have shown that social behavior can be analyzed at two levels in line with some of the research that analyzes to which degree personality is an inherent trait and to which degree it is impacted by the specific social roles a person takes. The normative aspects of personality deal with the type of personality traits most individuals are expected to have especially if they are well adjusted psychologically, to fit well within their social network. To understand these aspects, we compute the behavior of the person's friends and followers. We find that some of these features are strong predictors of personality. The second aspect of personality are the traits that distinguish them from everybody else. To model this, we compute a large number of features. We also look at the informativeness of the person's behavior towards all their friends, whether they treat some friends similarly or differently. We find that some of these features are also strong indicators of personality. Our features are unique in the study of personality in social media and provide new insights to the use of social media sites likes Twitter.

There are several important areas of future work in this area. First, we need to improve our performance on several of the personality features, since it is unacceptably low for some, especially Neuroticism and Extraversion. Studies by Moskowitz and Zuroff [28], [29] indicate that the degree to which one varies behavior for a specific personality trait is positively related to neuroticism, and the variation across different traits is correlated with extraversion. This might account for the difficulty for predicting these dimensions. This may be improved with a larger subject pool, but may also involve the refinement of our measures by considering deviations from norm, i.e. friends and family. An important question is whether the typical use of Twitter does not allow the expression of these traits [15]. For example, in the time of unrest, uncertainty and risk, the expression of personality by behavior may display very different characteristics. Study of these is topic of future research.

We are also interested in using Twitter behavior to predict other data, particularly trust between users. Future experiments will require us to establish ground truth trust values, investigate which behavioral features relate to trust, and which machine learning algorithms work best.

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