Inferring Neuroticism of Twitter Users by Utilizing their Following Interests

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Abstract

Twitter is a medium where, when used adequately, users’ interests can be derived from what he follows. This characteristic can make it attractive for a source of personality derivation. We set out to test the hypothesis that, analogous to the Lexical hypothesis, which posits that word use should reveal personality, following behavior on social media should reveal personality aspects. We used a two-step approach, wherein the first stage, we selected accounts for whom it was possible to infer personality profiles to some extent using available literature on personality and interests. On these accounts, we trained a regression model and segmented the derived features using hierarchical cluster analysis. In the second stage, we obtained a small sample of users’ personalities via a questionnaire and tested whether the model from stage 1 correlated with the users from step 2. The explained variance for the neurotic and neutral neuroticism groups indicated significant results ($R^2 = .131, p = .0205; R^2 = .22, p = .0044$). Confirming the hypothesis that following behavior should be correlated with one’s interests and that interests are correlated with the neuroticism personality dimension.

1 Introduction

With the advent of massive data streams of personal online behavior, there has been a surge in interest in relating this behavior to classical constructs in psychology. In particular, the question of whether online behavior can be related to personality profiles obtained from psychometric personality instruments, often the Big Five (Digman, 1990), has led to a field of research that has been coined Personality computing (Vinciarelli and Mohammadi, 2014). Studies in this field have found significant correlations between personality scores and lexical elements in written text, such as essays (Mairesse et al., 2006), blogs (Oberlander and Nowson, 2006; Yarkoni, 2010; Minamikawa and Yokoyama, 2011; Iacobelli et al., 2011), self-presentations (Batrinca et al., 2011), emails (Estival et al., 2007), texting (Holtgraves, 2011), and even the choice of email addresses (Back et al., 2008).

The idea that an author’s personality is reflected in written or spoken text at all, is referred to as the Lexical hypothesis (Pennebaker and King, 1999; Mairesse et al., 2006), and has been confirmed in many studies. As personality involves and influences the interaction with one’s environment, it should be expected to influence other facets of linguistic and non-linguistic expression. The rise of social media over the last decade resulted in this interaction being partly transposed to digital platforms. In fact, the current omnipresence of social media have compounded to the availability of records of individual expression and extends well beyond just the textual, and includes Facebook “likes” (Kosinski et al., 2013), sharing behavior (Gou et al., 2014), website visiting behavior, YouTube videos (Biel and Gatica-Perez, 2012; Farnadi et al., 2013), LinkedIn profiles (Faliagka et al., 2012), Instagram pictures (Ferwerda and Tkalcic, 2018), and tweets on Twitter (Golbeck et al., 2011; Chen et al., 2014; Li et al., 2014).

At face value, Facebook, Twitter and other social media platforms seem quite similar. Indeed lexical hypothesis-driven approaches have treated Facebook status updates as more or less equivalent to Twitter tweets. However, there is an essential distinction between the purposes of the two media. Facebook is
generally used as a place to keep in touch with friends and acquaintances. Twitter, on the other hand, is a medium that is used for sharing and gaining information related to someone’s interests. As a result, to use Twitter adequately and benefit from its full set of features, an active Twitter user is forced to follow his different interests on Twitter. This characteristic of Twitter can make it especially attractive as a source for personality derivation, as preferences of individuals can, to a significant extent, be explained by underlying personality traits (Ozer and Benet-Martinez, 2006).

It has often been contended that the social network(s) that people find themselves embedded in is reflective of many personal characteristics (Kosinski et al., 2013). Social media networks —reflected in the connections users can make to other users, e.g., by ‘friending’ on Facebook or ‘following’ on Twitter— have been related to various personal characteristics such as gender, age, ethnicity, sexual orientation, religious and political views (Kosinski et al., 2013). Although it has been observed that various generic network metrics that do not take into account the node characteristics of the connected nodes, including connectedness, node centrality measures, as well as the total number of friends / followers and the number of users followed, are correlated with personality (Quercia et al., 2011; Li et al., 2014), to our knowledge, no research on computational personality has investigated whether the specific set of accounts followed by a Twitter user is associated with personality.

In this study we aim to investigate if, and how profiles of accounts followed by a user are related to personality. We do this by deriving a predictive model from Twitter following graph data related to a set of prior chosen interests, and validating this predictive model on a sample of Twitter users from whom we obtained personality profiles using a standardized test. We focused particularly on neuroticism, as it has shown to have a reliable correlation to social media extracted features (Blackwell et al., 2017; Abbasi and Drouin, 2019). The specific interest were chosen on the basis of available literature that relates the interest to personality, and on the requirement that this interest can be relatively easily inferred from Twitter accounts using heuristic methods. We hypothesize that the following of (clusters of) nodes in the Twitter graph (that we coin ‘influencer accounts’ below) are significantly correlated with personality scores on a standardized personality test.

2 Methods

To build a predictive model that uses the links between nodes, a large sample of users is required as predictor variables within all the possible connections in the following graph data. While it is easy to obtain a large sample of Twitter users and the information regarding their following behavior, it is not easy to obtain their personality profiles by having these users fill out a psychometric test. We therefore developed a two stage approach: In the first stage we select a large sample of Twitter users for whom it was possible to infer personality profiles to some extent by heuristic means from their expressed interests and professions (we detail this below). On this data set, we trained a regression model. In the second stage, we obtained a small sample of Twitter users who were willing to fill out a personality questionnaire (the NEO-FFI) to provide us with a validation sample: We tested whether the predictions by model from stage 1 for the people in our stage 2 sample significantly correlated with personality profiles obtained from the questionnaire they filled out.

2.1 Using specific interests as a personality gauge

In the first stage we used heuristic methods to build a regression model. In particular, we searched for Twitter users who expressed specific interests on their Twitter accounts that have been linked to personality characteristics in previous research. For instance, we searched for Twitter users who expressed interest in yoga as people participating in yoga tend to score lower on neuroticism than the general population (Venkatesh et al., 1994). Similarly, social interests have been correlated with agreeableness (Costa and McCrae, 1985); interest in self-enhancing or affiliating humor have been found to negatively correlate with neuroticism (Greengross et al., 2012); and entrepreneurial inclinations correlate negatively with neuroticism (Zhao and Seibert, 2006). Twitter users express these specific interests not only in their

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1Note that the difference between ‘friending’ and ‘following’ is another difference between Facebook and Twitter, in that the former is a symmetric relation, while the latter is unidirectional.
tweets, but also in the Twitter accounts that they follow. We will coin Twitter accounts followed by a user influencer accounts, or influencers for short, in line with the use of these terms in the field of marketing. Furthermore, such interests can be expressed in their profile in their occupational denomination, which is either announced in their profile or can possibly be inferred from the influencer accounts that they follow. Research showed that sort-alike interests, such as food consumption, brand-preference, and political preference could all be deducted from following behavior (Abbar et al., 2015; Chu et al., 2016; Golbeck and Hansen, 2014). Correspondingly, neuroticism is negatively associated with the Enterprising type of Holland’s RIASEC model of occupational interest (Armstrong and Anthoney, 2009; Holland, 1997; Costa Jr and McCrae, 1992; Zhao and Seibert, 2006). This way, an Enterprising-occupational preference can be used as a parameter for the emotional stable group.

Using a set of specific interests and occupations, we collected three large groups of together 6107 Twitter users that we could classify as more likely neurotic (NEU+), more likely emotionally stable (NEU-), and more likely neutral (NEU±) based on the influencers that these accounts follow. In particular, users in the neurotic group (NEU+) were found by searching for users interested in self help information for stress coping (Saper and Forest, 1987; Kessler et al., 1997), or artistic profession (Marchant-Haycox and Wilson, 1992; Gelade, 1997; Nowakowska et al., 2005; Srivastava and Ketter, 2010); users in the emotionally stable group (NEU-) where found by searching users who were interested in entrepreneurial topics (Zhao and Seibert, 2006; Brandstätter, 2011) or in self-enhancing humor (Greengross et al., 2012; Kuiper and Leite, 2010; Mendiburo-Seguel et al., 2015), while users in the neutral group were found by searching for users who were interested in topics from both these groups (e.g., both interested in yoga and in entrepreneurial topics). For finding the included Twitter accounts we extracted the followers of accounts resembling these particular interests via the Twitter REST API. The validity of the collection was assessed by verifying a random sample of a small number accounts from each group at face value. Example searches are presented in Table 1. The logic behind the neutral group entails that a user who is interested in both interests for the neurotic and emotional stable group, would be classified as neutral. Similar according to the NEO-FFI. However, this does result for the groups not being mutual exclusive. As a result, users who were in more than one group, were excluded from the data set. In Table 2, some examples of the used influencer accounts are given.

The collection of all these influencer accounts constitutes our set of predictors: Each influencer account defines a dummy variable that is equal to 1 for users who follow this influencer, and 0 for users who do not follow this influencer. Because this results in a very large set of dummy variables (over 20,000), we clustered them into a limited set of 100 influencer clusters by means of (complete linkage) hierarchical clustering (McQuitty, 1955), and scored each user on these groups by counting the number of accounts in each influencer clusters a user followed. Hence, our data set for stage 1 consisted of 18,000 Twitter users, divided over three inferred neuroticism groups, for each of which we had as predictive features their count scores for the 100 different influencer clusters.

### 2.2 Feature selection

Using this first stage data set, we built a regression model in order to determine which of the 100 influencer groups count features were important for the prediction of neuroticism. We used multinomial least absolute shrinkage and selection operator (Lasso) regression (Tibshirani, 1996) to predict neuroticism group membership from these features. Lasso regression penalizes regression coefficients by adding their absolute values to the least squares criterion, weighted by a regularization strength parameter. This penalty promotes coefficients to be exactly equal to zero that would have been close to zero in normal regression. The non-zero coefficients of the resulting model defines the set of relevant features. This, in effect, automatically selects the features that are relevant for distinguishing between the neuroticism groups. How many coefficients end up at zero depends on the regularization strength parameter. We used 10-fold cross-validation to determine the optimal regularization strength (Friedman et al., 2010).

### 2.3 Model validation

In order to validate the influencer group count features derived from the first stage data set, and in order to test the hypothesis that personality is correlated with Twitter following behavior, we conducted ordinary
Table 1: Overview of example queries used in order to create groups reflecting different dimensions of neuroticism.

| Group               | Query                                                                 |
|---------------------|----------------------------------------------------------------------|
| Neurotic group      | SELECT * FROM SAMPLE WHERE user follows >= 3 Stress coping influencers OR >= 3 Artistic profession influencers |
| Emotional stable group | SELECT * FROM SAMPLE WHERE user follows >= 5 Enterprising influencers OR >= 3 self-enhancing humor influencers OR >= 5 Yoga influencers |
| Neutral group       | SELECT * FROM SAMPLE WHERE user follows >= 3 Enterprising influencers AND 3 Stress coping influencers OR >= 3 self-enhancing humor influencers AND >= 3 Artistic profession influencers |

Table 2: In this table, we can find some examples of influencers used to generate the three different groups. The neurotic influencers depict anxiety, self-help, and stress-coping accounts, which aim to help people with negativity in their lives. The emotional stable influencers found were mostly connected to entrepreneurship. The word *ondernemer* is dutch for entrepreneur. ZZP an organization connected to freelancing and MKB, stands for middle and small companies, supports entrepreneurial companies. Note that these are just some examples to give a general idea of what kind of accounts were categorized as influencers.

| Group                        | Influencers                                                                 |
|------------------------------|-----------------------------------------------------------------------------|
| Neurotic influencers         | @WakeupPeople, @suicidalwrck, @sosadtoday, @depressingmsgs, @AgainstSuicide, @depression |
| Emotional stable influencers | @ondernemer24, @nieuws_4_zzp, @de_ondernemer, @GreenBiz, @MKBNL, @FinancialTimes |

3 Results

3.1 Feature extraction: Clustering and Lasso regression

The database queries yielded a total of 6107 twitter users divided into 2301 NEU+, 1156 NEU±, and 2650 NEU- accounts. All subsequent data processing was conducted in R (R Core Team, 2019). These...
6107 Twitter users followed a total number of 669104 unique influencer accounts. To reduce this number of potential predictive features, we first removed the influencer accounts from that had near zero variance (Kuhn and Johnson, 2013, those that were either followed by less than 1% or not followed by less than 1%). This reduced the set of 669104 influencer accounts to 4367 potential predictive features. We then reduced the number of predictive features further by means of agglomerative hierarchical clustering with complete linkage as cluster dissimilarity measure (Venables and Ripley, 2013) on the basis of similar follower patterns across the 6107 Twitter users. The output yielded 100 influencer group count clusters of varying sizes, ranging from just a few Twitter accounts to nearly 200. Subsequently, we used multinomial lasso regression (Tibshirani, 1996) to find the influencer group count clusters that are most predictive for group membership. Before fitting the multinomial lasso regression model, the influencer group count features were standardized to have zero means and unit standard deviations. The lasso-penalty strength was fine tuned with 10-fold cross-validation to optimize the predictive classification accuracy. The cross-validated prediction accuracy of this model was more than 90%, indicating that the NEU+, NEU±, and NEU- groups could be well separated. Of the 100 influencer group count features that entered the multinomial lasso regression, 76 had non-zero coefficients on at least one of the multinomial predictive functions. Only 46 of these were considered of predictive importance: influencer features with a regression coefficient of at least 10% of the largest coefficient in absolute value.

3.2 Validation: Multiple linear regression

130 Twitter users filled out the personality questionnaire. Participants were excluded if they did not complete the survey, or had protected Twitter accounts. In total, 98 participants were eligible.

We admitted the influencer group count features selected by the multinomial lasso regression to a multiple linear regression analysis in which the NEO derived neuroticism score was used as the dependent variable. We did this separately for each of the three prediction functions for the NEU+, NEU±, and NEU- groups in the previous step. While for the NEU± and NEU- group equations the explained variance was significant at the .05 level, $R^2 = .248$, adjusted $R^2 = .131$, $F(18, 84) = 2.125$, $p = .0205$, and $R^2 = .38$, $F(20, 77) = 2.328$, $p = .0044$, respectively, the explained variance for the NEU+ equation was only marginally significant, $R^2 = .261$, adjusted $R^2 = .104$, $F(17, 80) = 1.66$, $p = .068$. Note that these tests evaluate different predictive equations because they include mostly non-overlapping sets of influencer group count features. The influencer Twitter handles (i.e., their ‘@’ names) that are associated with significant coefficients are displayed in Table 3. The significant coefficients for the NEU± and NEU- regressions were mostly negative, indicating that with increasing counts on the corresponding features (i.e., with increasing number of influencer accounts followed within the feature cluster) the neuroticism score decreased. Hence, these regression models are mostly indicative of emotional stability. The only regression coefficient that was significant in the NEU+ equation was positive.

We did various diagnostic checks on these regressions (Fox, 2015; Fox and Weisberg, 2018). Because influence measures indicated some of the cases to be influential, we also ran the regression analyses with these influential cases removed. For all three equations, this only had the effect of making the observed effects larger, and the $p$-values smaller—indeed rendering the previously marginal significance of the NEU+ regression model highly significant ($R^2 = 0.346$, adjusted $R^2 = 0.207$, $F(16, 75) = 2.48$, $p = .004$), while the NEU± and NEU- models maintained high levels of significance ($R^2 = 0.3$, adjusted $R^2 = 0.184$, $F(13, 79) = 2.6$, $p = .0004$, and $R^2 = 0.457$, adjusted $R^2 = 0.306$, $F(20, 72) = 3.025$, $p = 0.0003$, respectively).

Because it has been previously reported that the number of Facebook ‘friends’ is associated with personality, we verified that adding a total number of following accounts feature did not change any of the models, $\Delta R^2 = 0.01$, $F(1, 79) = 1.134$, $p = .29$ for the NEU+ model, $\Delta R^2 = 0.017$, $F(1, 83) = .025$.
1.957, \( p = .165 \) for the NEU+ model, \( \Delta R^2 = 0.007, F(1,76) = 0.812, p = .371 \) for the NEU- model. Also, a separate regression of the neuroticism score on this feature did not yield a significant explained variance, \( F(1,96) = 0.03061, p = .862 \). In addition, because the influencer accounts that are associated with significant coefficients were mostly related to entrepreneurial interest and self-employment, we checked whether the significant predictive power of the models simply resulted from entrepreneurial interest by adding the count totals of the number of accounts participants followed that were also followed by Twitter users in the NEU- group. This also did not lead to a significant change of models, \( \Delta R^2 = .002, F(1,79) = 0.254, p = .642 \) for the NEU+ model, \( \Delta R^2 = .01, F(1,76) = 1.065, p = .305 \) for the NEU± model, and \( \Delta R^2 = .002, F(1,76) = 0.217, p = .642 \) for the NEU- model; nor did a separate simple regression of the neuroticism scores on this feature yield a significant effect (\( F(1,96) = 0.031, p = .861 \)). Hence, taken together these results indicate that it is not merely the number of account followed, nor merely an entrepreneurial interest that is able to explain the variance in the neuroticism scores, but the specific pattern of influencer groups that are followed. A series of similar regressions in which the other personality scores (openness, conscientiousness, extraversion, and agreeableness) were used as dependent variables did not result in significant omnibus tests, which shows that the results are particular to neuroticism for which we constructed our influencer group count features.

| Group  | Relation | (example) Accounts                                                                 | Cluster Size |
|--------|----------|------------------------------------------------------------------------------------|--------------|
| Neu+   | Positive | @9GAG, @9GAGTweets, @Rossren, @OhDailyJustin                                     | 4            |
| Neu±   | Negative | @JOR_ID, @BoogerdLive, @TeamSunweb, @RobScheepers, @lars_boom                      | 14           |
| Neu±   | Negative | @MINOCW, @Leraar24, @SanderDekker, @LerarenMetLef, @JelleJolles                    | 25           |
| Neu+   | Positive | @bibliothek, @NPO2extra, @NOGvacatures, @taalmissters, @vangoghsmuseum             | 21           |
| Neu-   | Negative | @StephenRcovey, @MarcStijfs, @woutsmelt, @TonyRobbins, @Upgres                     | 17           |
| Neu-   | Negative | @Politie_Zeeland, @zeelandzakelijk, @JoAnnesdeBat, @hvzeeland, @PetraBoevere       | 22           |
| Neu-   | Negative | @OP_Nederland, @KVK_NL, @AccWeek, @Taxence, @BDONederland                         | 32           |
| Neu-   | Positive | @Sebastiaan_IMG, @Brandpunt_plus, @nieuwelente, @StudioLizix, @TL_070               | 19           |

Table 3: Influencer account handles (‘@’ names) associated with the influencer group count features with significant multiple regression coefficients in the validation data set. Top row: Features that predict NEU+ membership. Middle rows: Features that predict NEU± membership. Bottom rows: Features that predict NEU- membership. Only features with significant multiple regression coefficients are displayed. For each cluster, we indicate whether it had a negative (i.e., indicate lower neuroticism score) or positive (i.e., indicate higher neuroticism score) coefficient. We show five arbitrary chosen accounts per cluster.

4 Discussion

We set out to test the hypothesis that, analogous to the Lexical hypothesis which posits that word use should reveal personality, following behavior on social media should reveal aspects of personality. This hypothesis was motivated by the fact that following behavior should be highly correlated with one’s interests and occupation, and that interests and occupation are correlated with personality dimensions. In particular, we aimed to test this hypothesis with respect to the degree of neuroticism of an individual. To do so, we introduced a novel technique for constructing predictive independent variables: On the basis of these well established correlations between personality on the one hand, and interests and occupation on the other, we were able to gather a sufficiently large database of Twitter users and their following behavior to extract clusters of influencer accounts that discriminate between Twitter users that have a lower or
higher propensity to score high on the neuroticism dimension of the Big Five. Using these predictors we were then able to confirm the hypothesis by showing that these predictors were significantly related to neuroticism scores in a relatively small sample of 98 participants recruited to fill out the NEO-FFI.

On the basis of these results we can conclude that it is possible to derive estimates of neuroticism from following behavior. A significant consequence of these findings is that, in contrast to personality profiles extracted on the basis of lexical hypothesis which requires active engagement of social media platform users, our results are purely based on information that is passively conveyed by Twitter users by their following behavior. Hence, a neuroticism score can be obtained even from social media users who do not actively engage in information sharing on these platforms. One might object that the explained variance is rather low and consequently, very imprecise. This is certainly true for assessing specific individuals reliably—that is, our results do not really support the notion that it is possible, e.g., for employers to screen a specific applicant for a job. However, it is sufficient for targeting population segments; e.g., it allows for talent recruiters to target subgroups of the population that are more likely to have certain personality profiles, or for marketeers to target population segments, e.g., in attempts to sway an election.

4.1 Time and Location

A relevant note for this study is that its results are subject to time and location. This is because individual interests can be prevalent during a specific period or at a particular location. For instance, yoga or meditation are rising interests, which are now much more popular than several decades ago. These interests were used as neurotic features (i.e., influencers). However, regarding their rising popularity, they might not be significant features in the future, as then all kinds of people would be interested in performing yoga or meditation. In respect to location, the interests used are subjective to Dutch nationals, and more or less the Western world. The neurotic interests might be different in other parts of the world. Not to mention that personality determination in itself works differently in other parts of the world, for instance, Asia (Markus and Kitayama, 1998). Therefore, the results from this study are dependent of time and location.

4.2 Caveats

It is not clear what population our sample represents, as it is a self-selected group. Also, Twitter suggests a user which accounts to follow based on the accounts the user already follows. This causes accounts to be clustered due to Twitter’s recommender system. Furthermore, concerning the choice of interests and occupations for deriving our prediction variables, we limited our database to Twitter users consisting of entrepreneurial or artistic users, or expressed interest in yoga, stress coping, or certain types of humor. Needless to say, this is a minimal set of expressed interests and/or occupations. Although the validation set was not selected on the basis of these criteria and the results should generalize to a broader population of Twitter users, we anticipate that a broader range of topics of interest and/or occupations that have been shown to be correlated with personality aspects will potentially improve and extend personality profiling concerning Twitter following behavior.

4.3 Privacy

Lastly, an interesting point worth mentioning is that more and more aspects of the digital footprint of individuals present pile up to attributing variance in the process of personality computation. This way, it becomes increasingly likely that a complete combination of all an individual’s social media activity could be quite an accurate determinator for one’s personality. Because of this, it becomes increasingly important to think about the privacy legislation of different media. Twitter provides the opportunity to protect your account, and this way, your shared information cannot be extracted using the Twitter API. Every media should offer the option for a user to make his or her data private. Hence, if it is not in human’s interest to have every individual’s personality available on the web or in the hands of a few corporations, it will become imperative that legislation forces this option to be mandatory.
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