On the Role of Personality Traits in Followee Recommendation Algorithms

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Abstract Followee recommendation is a problem rapidly gaining importance in *Twitter* and other micro-blogging communities. Most traditional recommendation systems only rely on content or topology, disregarding the effect of psychological characteristics over the followee selection process. As personality is considered one of the primary factors that influence human behaviour, this study aims at assessing the impact of personality in the accurate prediction of followees. It analyses whether user personality could condition followee selection by combining personality traits with the most common followee recommendation factors.

1 Introduction

Recommendation systems are present in a wide range of applications that present users with enormous sets of items or services [11]. They aim to assist users in efficiently finding relevant items or people by providing personalised advice in the form of ranked lists. The exponentially increasing volume of online activity in micro-blogging sites makes the development of accurate followee recommendation systems distinctly relevant. As users might have several different reasons for choosing their followees, understanding such reasons becomes fundamental for designing personalised recommendation strategies. For example, a user might choose to follow other users because they are co-workers, others because they publish interesting information, others because they are celebrities, or others because they share the same interests, among other plausible explanations.

Although personality is acknowledged as one of the most important factors that can affect human behaviour and social relationships, its effect is generally disregarded. Most recommendation systems rely only on content and topology, neglecting psychological characteristics' effect over users' preferences and decisions. This study aims at measuring the impact of personality in the accurate prediction of followees beyond common recommendation factors. To this end, the behaviour and characteristics of users, denoted by their own distinguishable personality, are combined with two common factors influencing followee selection in *Twitter.* A strategy for quantitatively assessing the matching degree of personality between two users is also defined in this study. Then, the combination of personality with each of the recommendation factors considered is inserted into a recommendation algorithm to compute the similarity between a target user and each potential followee to recommend.

The rest of this paper is organised as follows. Section 2 describes personality-based followee recommendation approaches. Section 3 introduces the followee recommendation problem, and describes both the traditional factors and the usage of personality for followee selection. Section 4 describes the *Twitter* data used for experimentation. Section 5 describes the quantitative assessment of users' personality and how to combine it with traditional followee recommendation factors. Section 6 assesses personality impact on followee recommendation. Section 7 summarises the conclusions of this study.

2 Related Work

Most recommendation systems focus on developing better algorithms, instead of investigating new factors to be added to the recommendation process. In [30] personality scores were added to a content-based movie recommendation system. To assess the personality impact on recommendations, the authors developed two systems. The first one used personality to positively adjust item diversity, whereas the second recommended items regardless user's personality. The second system aimed to analyse whether people would have negative opinions if the recommendation diversity did not match their personality. Most of the 52 analysed users declared that the first system was more helpful as it showed recommendations that match their interests. However, as the approach was not compared with non-personality based systems, it cannot be guaranteed to outperform traditional recommendation systems.

In [12, 26] personality scores were included as complementary information in collaborative recommendation systems. Both relied on a explicit assessment of personality. In [12] experimental evaluation was based on 111 users of the DiscoverMusic dataset [13]. The approach was compared to a traditional recommendation system, showing that the approach significantly outperformed systems solely based on either ratings or personality features. Additionally, the approach helped to solve the cold-start problem when offering recommendations to new users or in sparse datasets. In [26] user similarity was measured by computing the Euclidean distance between the personality scores across the five dimensions. Experimental evaluation based only on 52 users showed that personality-based recommendations outperformed rating-based ones.

These approaches share the same drawbacks. First, they included a relatively small number of users, preventing the generalisation of results. Second, personality is self-assessed, which not only requires explicit participation of users, but also could result in biased scores. Users' view of themselves might not reflect their actual behaviour and, in turn, their real personality [23]. Finally, they were tested in the context of item recommendation using collaborative filtering techniques, none of the works tested the approach in the context of user recommendation in social networks. Consequently, the impact of personality in social recommendation systems is yet to be proven.

3 Followee Recommendation

In the context of social networks, recommendation systems can be used to suggest users worth following. This can be seen as a link prediction problem [14], i.e. the problem of inferring which user interactions are likely to occur in the short-time.

Most of the existing followee recommendation systems on micro-blogging platforms rely on either topological or content-based factors, [10, 21], for example [1, 10]. Content-based link prediction suggest users based on the textual or topical similarity. In turn, link prediction based on topological factors aims at suggesting users to a target user based on a comparison of their neighbourhoods.

3.1 Content-based Factors

As users can subscribe to the content their followees publish, it becomes a valuable factor for link prediction, i.e. a user is likely to have a link with other users sharing the same information preferences [20]. Users' interests can be characterised by means of profiles based not only in the published tweets, but also in the tweets a user has marked as favourite or has re-tweeted. Whereas the first alternative indicates the interests of users in terms of the information they create and publish, the last two indicate the interests of users in terms of the information they read and consider interesting. These profiles will be referred as *publishing profile* and *reading profile* respectively.

The set of tweets t for a user u_j can be denoted as: $tweets(u_j) = \{t_i, ..., t_n\}$. The *publishing profile* of a user is built by considering all of the user tweets under the assumption that users tend to tweet about things that are relevant to them. Formally, the profile of user u_j can be defined as: $pub - profile(u_j) = tweets(u_j)$. Finally, the *reading profile* of a user u_j can be defined by considering the tweets the user has re-tweeted: $read - profile_{RT}(u_j) = tweets_{RT}(u_k) \forall k \in followees(u_j)$.

The final representation of profiles comprises all terms appearing in all tweets weighted according to their frequency. Once the profiles are built, the cosine similarity metric is used for computing the similarity between them. In the case of content-based followee recommendation, an algorithm should match the *reading profile* of a user with the *publishing profile* of their potential followees.

3.2 Topological Factors

Most link prediction algorithms are based on network topology, typically by computing node similarity using users' neighbourhoods or ensembles of paths. Common metrics applied to *Twitter* are the number of common followees (assuming that if two users follows the same people their are likely to share interests) and Sørensen similarity (among other local similarity indexes [15]). They can be respectively defined as $\frac{|\Gamma_{out}(x)\cap\Gamma_{out}(y)|}{\Gamma_{out}(x)\cup\Gamma_{out}(y)}$ and $\frac{2|\Gamma(x)\cap\Gamma(y)|}{k_x+k_y}$, where x and y are nodes, $\Gamma(x)$ is the set of x's neighbours, $\Gamma_{out}(x)$ is the set x's followees, $\Gamma_{in}(x)$ is the set of x's followers, and k_x is x's degree.

3.3 Personality

Psychology defines personality as a set of emotional, attitudinal and interpersonal processes specific to each person, and several temperamental and behavioural response patterns [9]. Consequently, personality can be considered one of the most important factors influencing behaviour, as it moderates how people behave, interact and react to other individuals. Several authors [6, 7] have agreed that personality remains stable during adulthood, exhibiting considerable continuity and stability over time. As a result, a single assessment might be enough for predicting personality in the medium term. Social environments can encourage personality manifestation as they satisfy all the basic psychological needs, such as relatedness, competence and autonomy [24]. Moreover, there is a relation between personality, and the interests and preferences of individuals [8], implying that individuals with similar personalities might have similar interests.

Several authors aimed at defining personality by means of a set of features or characteristics. Tupes and Christal [27, 28] identified five recurrent features describing personality. Later works [17, 18] offered evidence of those features, thus confirming the findings. As a result, personality can be expressed via the Big Five model [5], which hierarchically defines it as a composition of five traits or dimensions. The model defines some of the most essential aspects of personality, even though its theoretical foundations have been objected [2]. *Agreeableness* refers to being sympathetic, cooperative and helpful towards others. *Extraversion* refers to being outgoing, friendly, assertive and energetic. *Openness to Experience* refers to being curious, intelligent and imaginative. *Conscientiousness* refers to being organised, persevering, disciplined, achievement-oriented and responsible. Finally, *Neuroticism* refers to being anxious, insecure, moody, and sensitive. This last dimension also refers to the Emotional Stability, anxiety and impulse control of individuals.

Social networks can be considered a manifestation of relationship patterns between individuals that, as their real-world counterpart, evolve over time. Modifications in the relational patterns could be caused by the reciprocity and transitivity in structural and network mechanisms, structural competition, or they could be related to the particular characteristics of individuals [25]. In this regard, the impact of the Big Five personality dimensions on social relationships and friendship selection was studied in [8, 22]. Both studies concluded that the different dimensions have an important and differentiated role in the selection of friends, the size of the group of friends, and the similarity between friends across the personality dimensions. For example, Agreeableness, Extraversion and Openness to Experience emerged as significant predictors of friendship ties, as individuals tended to select friends with similar personality scores across those dimensions. Although Extraversion was declared the most important factor affecting friendship selection, Agreeableness individuals were able to attract more friends. Neither Conscientiousness not Neuroticism were related to the establishment of new relationships. Furthermore, Neuroticism individuals resulted more interested in maintaining relationships. Finally, results suggested that the similarities across the different dimensions had a greater impact on friendship selection than the overall similarity computed considering all dimensions.

4 Data Collection and Processing

A *Twitter* dataset was created by crawling 1,852 seed users extracted from[1]. Every selected seed user had to list the language account as English, and at least 10 followees and 10 published tweets. For those users, all tweets, followees, followers and favourites were retrieved. The same data was retrieved for all of their followees. In total, 547,180 users were crawled comprising 1,060,593,898 tweets (1,939 tweets per user in average) and 1,540,441,846 followee relations (2,816 followee relations per user in average).

Two text processing approaches were defined, the first considered the full-text of tweets ($FULL$), whereas the second considered a pre-processed version of tweets(*PROC*). For the second approach, tweets were lexically and syntactically pre-processed. First, to guarantee language uniformity, all non-English tweets were removed based on the algorithm presented in [3][2]. Second, a probabilistic Part of Speech (POS) tagging was performed based on the tool defined in[3]. Only those tokens labelled as nouns or verbs were selected. Stop-words were removed from the remaining text using the lists proposed in[4] and[5]. Finally, the Porter Stemmer algorithm [19] was used to reduce syntactic variations, and thus improve the probability of finding similarities between profiles. Each seed user's personality score for the five dimensions was automatically computed by means of the classification methods and tool developed in [16]. SMOreg, a Support Vector Machines for regression was the model selected for computing the scores as it was reported to achieved the most accurate results for big data corpora [16].

5 Exploring Personality for Followee Recommendation

This study aims at analysing how user personality can condition followee selection by combining personality traits with commonly used factors in followee recommendation. Such combination of factors is inserted into a recommendation algorithm that computes the similarity among seed users and each potential followee, and then ranks those potential followees in decreasing order of similarity. This section presents the analysis performed to quantitatively assess the personality relation between users and their potential followees (Section 5.1), and defines the strategy applied to combine all the factors for performing the followee recommendation (Section 5.2).

5.1 Quantitatively Evaluating Personality

In order to assess the personality matching between a target user and each of his/her potential followees, the scores corresponding to each personality dimension, must be summarised into a unique personality matching score. An overall similarity measure (such as the cosine similarity) might not be adequate for computing the similarity, as it might result in high scores when the values for at least one of the compared dimensions are similar, regardless the score of the other dimensions. Thus, this study defines a strategy that considers personality scores' statistical distribution for the five separate dimensions. It consists of a similarity matching rule set, one for each personality dimension, with scores in the $[0, 1]$ range. Each rule models the compatibility of two users based on a personality dimension, e.g. an Extraversion rule would assign 1 to two users if both Extraversion scores are higher than 5, whereas it would assign a matching score of 0.5 if only one of them has a score higher than 5. The overall personality matching score is computed as the average of the individual dimensions scores. Conscientiousness and Emotional Stability dimensions are ignored as [8, 23] did not report significant effects on the friendship selection processes.

Each rule analyses the personality score of the potential followees in relation to the statistical distribution of scores of the actual user followees. In this context, if users tend to relate with users in a certain range of personality scores for a certain dimension, other users scoring in the same range should be preferred over users falling outside the range. Then, this strategy

[1] http://konect.uni-koblenz.de/networks/munmun_twitter_social
[2] http://odur.let.rug.nl/vannoord/TextCat/
[3] http://www.ark.cs.cmu.edu/TweetNLP
[4] http://www.ai.mit.edu/projects/jmlr/papers/volume5/lewis04a/all-smart-stop-list/english.stop
[5] dev.mysql.com/doc/refman/5.7/en/fulltext-stopwords.html

rewards those followees whose score is contained in the central 50% of the score distribution, i.e contained in the interquartile range. Considering that the interquartile range is not based on the supposition of a symmetric distribution of data, it is not as influenced by data outliers as the mean is. Consequently, the interquartile range is a more adequate and robust statistic for skew data, or when the exact characteristics of data distribution are not known in advance. For each rule, the highest matching score is achieved in those cases in which the personality score of the potential followee is contained in the interquartile range. Otherwise, the matching score is zero.

5.2 Combining Factors for Followee Recommendation

Once the potential set of followees for a specific seed user is selected, the algorithm computes the similarity between each pair of users. As this study aims at analysing how the selection of followees is affected by psychological characteristics, the recommendation algorithm needs to combine the topological and/or content-based factors with the matching personality scores. Consequently, the similarity between a user and a potential followee must be unified to obtain a similarity ranked list.

In this work, the different factors for followee recommendation were linearly combined as it is one of the simplest and most effective methods for combining multiple scores [29]. It also offers certain flexibility as different weights are assigned to the individual scores in order to improve the final score. Several weight combinations for each factor are analysed in the reported experiments to determine their optimal weights. The summation of each combination of weights is constrained to 1.

6 Measuring the Impact of Personality

For measuring the impact of personality on followee recommendation, an algorithm for ranking users by their similarity and selecting the top-*N* users was used. For each user, the actual user followees and a set of randomly selected non-followed users equivalent to the double of the number of actual followees were added to the pool of potential followees to be recommended. The recommendation algorithm selects the best ranked users in the pool, and the evaluation measures whether the algorithm was capable of identifying those users who already were considered interesting.

The top-*N* recommended users were selected for computing the overall precision and assessing the quality of recommendations. As there is no explicit feedback from the seed users available, the quality evaluation assumes that items that were not originally part of the followee set are uninteresting for the user. This assumption might not be accurate as recommended users might not be in the followee list simply because the user was unaware of their existence. As a result, the number of false positives, might be over estimated leading to an underestimated precision. For all the experimental evaluations, *N* was set to 5, 10, 15, and 10%, 15% and 25% of the ranked list of recommendations.

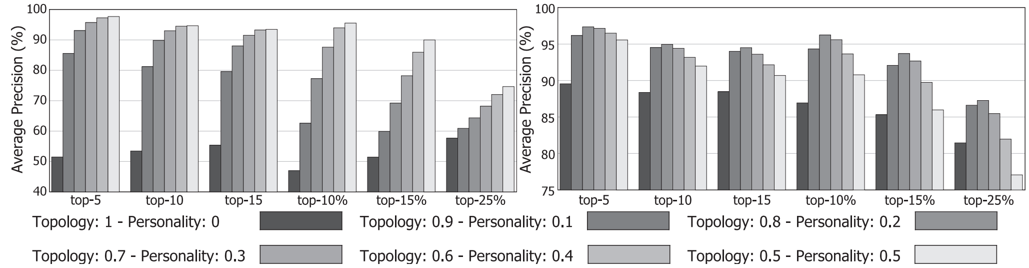
The statistical significance of precision results was evaluated according to the definitions and methods proposed in [4]. For each combination of followee recommendation factors, the statistical significance of the precision results was tested in order to determine whether result differences were significant and not due to a random or sampling error. In all cases, the null hypothesis was rejected, implying that personality had a significant and non-incidental effect on results regarding the precision achieved when recommending followees solely based on topology or content.

6.1 Personality and Content-based Followee Recommendation

Figure 1 summarises the average precision for each of the pre-defined *N*, including results for six linear combinations of factor's weights. Adding a quantitative analysis of personality had a positive impact on the precision for all *reading profile*s. In all cases, increasing the personality weight improved followee recommendation precision. Maximum precision, when considering $read-profile_{RT-PROC}$ was achieved with a personality weight of 0.2 and selecting the top-5 followees. Thus, it can be stated that considering a quantitative analysis of personality in combin-

Figure 1: Average Precision of Content-based Followee Recommendation

(a) $read-profile_{RT-FULL}$ (b) $read-profile_{RT-PROC}$



ation with content-based factors could help to correctly place the most important or interesting users in the first positions of the similarity ranking.

Figure 2: Precision Differences at top-25% for Personality and $read-profile_{RT-PROC}$ Combinations

(a) Content-based: 0.9 Personality: 0.1 (b) Content-based: 0.5 Personality: 0.5

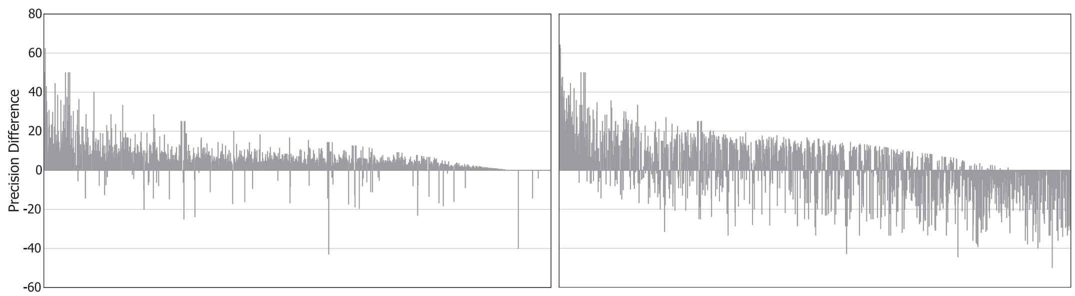


Figure 2 shows the precision per user with the $read-profile_{RT-PROC}$, for two of the evaluated linear combinations of weights. Only the results for the top-25% recommended followees are reported. Each figure shows the seed users sorted in ascending order according to the precision achieved when only considering content (plotted in X-axis). In the Y-axis, values above zero indicate that combining personality with content-based factors improved precision, whereas values below zero indicate that such combination did not improve the recommendations achieved solely based on content-based factors. As it can be observed, personality improved precision results for the majority of users for low values of personality weight. On the contrary, as the personality weight increased, precision results tended to decrease for those users with high precision results solely based on the content-based factor (users in the highest X-axis values). Considering personality and the content-based factor with equal weight tended to decrease precision with respect to content-based recommendation alone. These results imply that personality is an important factor to consider for recommending potential followees, and impose a limit to the weight that can be assigned to personality to improve results, as assigning weights that are higher to such limit could decrease the precision of recommendations.

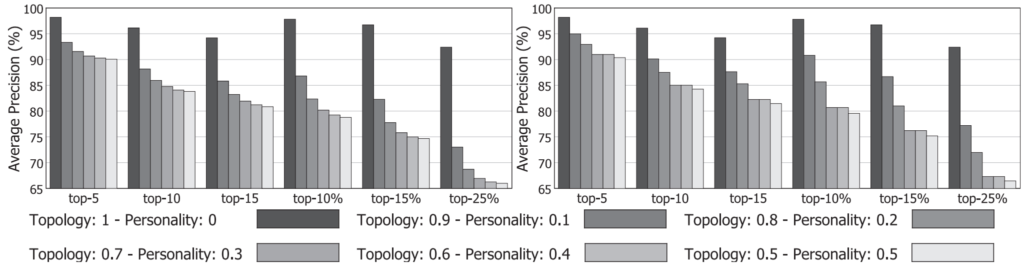
6.2 Personality and Topological Followee Recommendation

Figure 3 summarises the average precision for each of the pre-defined N and the six linear combination of factor's weights. Adding a quantitative analysis of personality had a negative impact on the recommendation precision for all the proposed topological metrics, as precision decreased. Although personality seemed to be an important factor when combined with content-based factors, it did not have the same effect on topological factors. Alike the previous case, combining topology and personality achieved maximum precision when considering low personality weights, i.e. 0.1.

Figure 4 shows the precision per user for the topology metric that achieved the best results (Sørensen index) for two of the evaluated linear combination of weights. Only the results for the top-25% recommended followees are reported. Each figure shows the seed users sorted according to the precision achieved when only considering the topology factor (plotted in X-axis).

Figure 3: Average Precision of Topology-based Followee Recommendation

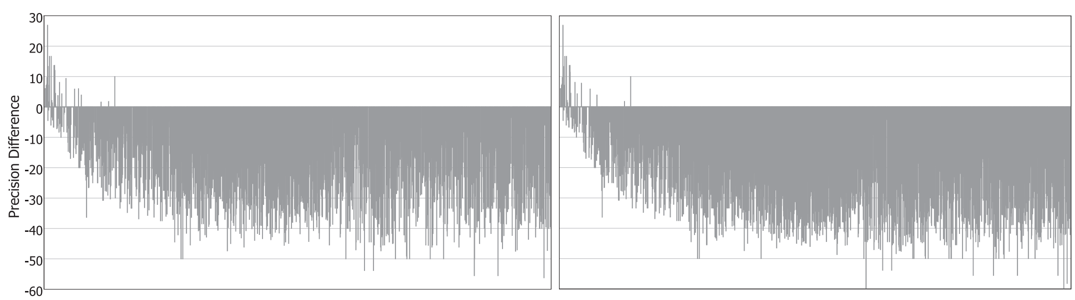
(a) Common Neighbours (b) Sørensen



Unlike when combining content and topology, combining topology and personality did not lead to precision improvements for the majority of users. However, when the precision solely based on topology was lower than 0.66 (users in the left of the X-axis), adding personality resulted in high precision improvements for all the analysed linear combination of weights. Alike for the content-based factors, as the personality weight increased, the differences tended to worsen. These results reinforce the fact that there is a limit to the weight that should be assigned to personality in order to either improve precision results or at least avoid reducing them.

Figure 4: Precision Differences at top-25% for Personality and Sørensen Combinations

(a) Topology: 0.9 Personality: 0.1 (b) Topology: 0.5 Personality: 0.5



7 Conclusions

The accurate suggestion of followees arises as a crucial issue give n the exponential number of active users in micro-blogging sites. Thus, the criteria for guiding the search and ranking of candidate users has to be carefully analysed. Most recommendation systems solely rely on topological or textual analysis, disregarding the effect of psychological characteristics, such as personality, over the followee selection process. This study analysed how user personality can condition followee selection by combining its quantitative analysis with commonly used factors for followee recommendation.

Results showed that personality should be considered as a distinctive factor for followee selection in content-based social networks,\sse such as *Twitter*. An accurate appreciation of commonly used factors (particularly content-based factors) tied to a quantitative analysis of personality is crucial to guide the search of potential followees, and thus, improve recommendations only based on such factors. Moreover, results showed the existence of a limit to the importance that should be assigned to personality in order to either improve precision results or at least avoid their reduction.

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