Engineering Applications of Artificial Intelligence 51 (2016) 24–36

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Personality-aware followee recommendation algorithms: An empirical analysis

Antonela Tommasel *,[1], Alejandro Corbellini [1], Daniela Godoy [1], Silvia Schiaffino [1]

ISISTAN Research Institute, UNICEN University, Campus Universitario, Tandil (B7001BBO), Argentina

ARTICLE INFO

Available online 29 January 2016

Keywords:
Followee recommendation
Twitter
Human aspects recommendation
Personality traits

ABSTRACT

As the popularity of micro-blogging sites, expressed as the number of active users and volume of online activities, increases, the difficulty of deciding who to follow also increases. Such decision might not depend on a unique factor as users usually have several reasons for choosing whom to follow. However, most recommendation systems almost exclusively rely on only two traditional factors: graph topology and user-generated content, disregarding the effect of psychological and behavioural characteristics, such as personality, over the followee selection process. Due to its effect over people's reactions and interactions with other individuals, personality is considered as one of the primary factors that influence human behaviour. This study aims at assessing the impact of personality in the accurate prediction of followees, beyond simple topological and content-based factors. It analyses whether user personality could condition followee selection by combining personality traits with the most commonly used followee predictive factors. Results showed that an accurate appreciation of such predictive factors tied to a quantitative analysis of personality is crucial for guiding the search of potential followees, and thus, enhance recommendations.

1. Introduction

Social networks and micro-blogging sites have increased their popularity in recent years, with hundreds of users joining everyday. Also, users spend more and more time on those sites sharing personal and relevant information and making new friends. In this context, finding high quality social ties becomes a difficult task due to not only the continuous expansion of micro-blogging communities, but also the difficulty of characterising users and their behaviour, which can influence their friend selection patterns. These situations lead to the imperious need of developing both accurate user characterisations and followee recommendation techniques.

In information-oriented social networks like *Twitter*, users might base their decision of starting to follow other users on several and distinctive reasons or characteristics. For example, a user might follow some users because they publish interesting information, others because they have the same interests, others because they are celebrities or popular individuals in the micro-blogging community, or even because they share some common friends, among other possible explanations. Consequently, understanding the reasons why a user selects who to follow becomes crucial for designing accurate and personalised recommendation strategies.

Although personality is considered as one of the primary factors influencing human behaviour, and thus, social relationships, most of the existing recommendation systems only rely on content and topological characteristics as predictive factors for followee recommendation. Thus, they neglect how users' interests and decisions are affected by psychological characteristics. This study aims at assessing the impact of personality in the accurate prediction of followees beyond simple topological and content-based factors. To this end, some of the most common factors influencing the selection of followees in *Twitter* are analysed in relation with each person's own behaviour and characteristics, denoted by their distinguishable personality traits.

The rest of this paper is organised as follows. Section 2 describes strategies found in the literature for personality-based recommendation in the context of traditional content-based and collaborative filtering recommendation systems, and the features commonly observed for predicting a user's personality. Section 3 introduces the problem of recommending who to follow in social networks. Section 4 describes the *Twitter* data used for experimentation. Section 5 presents the proposed strategies for

* Corresponding author. Tel.: +54 249 4439682x35; fax: +54 249 4439681.
E-mail addresses: antonela.tommasel@isistan.unicen.edu.ar (A. Tommasel), alejandro.corbellini@isistan.unicen.edu.ar (A. Corbellini), daniela.godoy@isistan.unicen.edu.ar (D. Godoy), silvia.schiaffino@isistan.unicen.edu.ar (S. Schiaffino).
[1] Also Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Argentina.

http://dx.doi.org/10.1016/j.engappai.2016.01.016
0952-1976/

quantitatively evaluating users' personality and how to combine it with other widely used followee recommendation factors. Section 6 measures the impact of introducing personality traits in a followee recommendation algorithm. Additionally, it discusses the statistical significance of the obtained results. Finally, Section 7 summarises the conclusions obtained from the performed experimental evaluation.

2. Related work

Most approaches for building recommendation systems focus on improving recommendation precision, instead of investigating how users are inherently influenced by their own personality, among other human factors that could influence the quality of suggestions. Wu et al. (2013) aimed at adding personality scores to a content-based movie recommendation system in order to generate more personalised and diverse recommendations. To assess the impact of personality in the recommendation process, the authors developed two systems. The first one used personality to positively adjust the item diversity, whereas the second one aimed at recommending items regardless of users' personality. The purpose of the second system was to analyse whether people would have negative opinions when the recommendation diversity did not match their personality. The study comprised 52 Chinese users who were asked to answer the Big Five test designed by Hellriegel et al. (1987), as well as to specify their movie preferences, and rate the recommended movies in both systems. Then, users were required to answer a questionnaire to express their overall opinions about the recommendation accuracy, system competence and overall satisfaction. The first system obtained significantly higher scores than the second one on every evaluated aspect. Particularly, most users declared that the first system showed recommendations that matched their interests, and that it was more helpful for discovering interesting movies. However, as the approach was not compared with non-personality based systems, it cannot be guaranteed to outperform traditional recommendation systems.

Hu and Pu (2011) and Tkalcic et al. (2009) presented approaches to include personality scores as complementary information in traditional rating-based collaborative recommendation systems. Both relied on the explicit assessment of personality through the Big Five test[2] and the IPIP[3] questionnaire respectively. Hu and Pu (2011) based their experimental evaluation on 111 users extracted from the DiscoverMusic dataset (Hu and Pu, 2010). The approach was compared to a traditional rating-based filtering system, showing that the system combining ratings and personality significantly outperformed the systems solely based on either ratings or personality features. Additionally, the approach was reported to help solving the cold-start problem when offering recommendations to new users or in sparse datasets. Tkalcic et al. (2009) proposed to measure the similarity of users in collaborative filtering by computing the Euclidean distance between the personality scores across the five dimensions. Two variants were compared, one considering only the neighbours of a certain user and the other considering all users. Experimental evaluation was based only on 52 users who were asked to rate several items to obtain their item-ratings profile. Results showed that the personality-based recommendation outperformed the rating-based one.

All of the presented approaches share the same drawbacks. First, they included a relatively small number of users, which prevents the generalisation of results. Second, personality was self-assessed through questionnaires, which not only requires the explicit participation of users but also could result in biased scores. The own view of themselves reported by users could not reflect their actual behaviour and, in turn, their real personality (Selfhout et al., 2009). Finally, the approaches were tested in the context of item recommendation using collaborative filtering techniques, none of the works include personality in the context of user recommendation in social networks. In consequence, the impact of personality in social recommendation systems is yet to be proven.

3. Followee recommendation problem

Social network data grows at an unprecedented rate due to the massive use of social networking sites. Millions of users have started to use micro-blogging sites since their beginning as a tool not only to propagate and share information, but also for finding new friends. Due to such exponentially increasing volume of online activity, effective recommendation systems are needed for guiding users in the search of useful and interesting items. 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 (Liben-Nowell and Kleinberg, 2003), i.e. the problem of inferring which user interactions are likely to occur in a short-time.

Most of the existing followee recommendation systems on micro-blogging platforms rely on either topological or content-based factors (Rowe et al., 2012). Link prediction based on content-based factors aims at suggesting users based on the textual or topical similarity with the target user, i.e. the user receiving the recommendations. In turn, link prediction based on topological factors suggests users to a target user based on a comparison of their neighbourhoods. Since this work is concerned with assessing the influence of user personality over these factors when selecting who to follow, Sections 3.1 and 3.2 describe respectively the content- and topology-based factors considered in this study. Finally, Section 3.3 introduces personality as a followee recommendation factor by stating its influence over social relationships.

3.1. Content-based factors

In micro-blogging platforms users can follow others and subscribe to the content they publish. Thus, content 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 (Romero and Kleinberg, 2010). The interest of a user can be characterised by means of profiles based on not only the content of the published tweets, but also the tweets a user reads. Whereas the first alternative indicates the interests of users in terms of the information they create and publish, the second one indicates the interests of users in terms of the information they consume, i.e. the information they choose to read and deemed as 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:

$$tweets(u_j) = \{t_i, \ldots, t_n\} \tag{1}$$

The *publishing profile* of a user is built by considering all 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:

$$pub\text{-}profile(u_j) = tweets(u_j) \tag{2}$$

The rationale behind the decision of building a *reading profile* is to adequately capture the preference and interests of users

[2] http://gosling.psy.utexas.edu/scales-weve-developed/ten-item-personality-measure-tipi/

[3] http://ipip.ori.org/

regarding the information they consume. According to homophily theories (McPherson et al., 2001), social interactions between similar individuals occur at a higher rate than among dissimilar ones. In the context of *Twitter*, if a user tends to read tweets of a certain topic, it is likely that he/she would like to follow users tweeting on those topics. However, followees might tweet on several topics, which might not be all interesting to users. Hence, it is necessary to identify the specific tweets that were interesting for a given user. *Twitter* provides users with two mechanisms for expressing their interest for other users' tweets. First, tweets can be marked as favourites. Marking a tweet as favourite is analogous as bookmarking a Web site. Second, tweets can be retweeted. Retweets are reposted or forwarded messages on *Twitter*. When a user makes a retweet, it is visible to all of his/her followers, i.e. the original tweet is then shared with more people. This is considered as the best mechanism to show interest and engagement on other users' tweets. As a result, tweets marked as favourites and retweets convey the information a user is really interesting in consuming. This leads to two alternatives for building the *reading profile* of a user u_j. First, a reading profile containing only the tweets marked as favourites ($tweets_{Fav}$), as Eq. (3) shows. Second, a reading profile containing only the tweets that a user has retweeted ($tweets_{RT}$), as Eq. (4) proposes:

$$read\text{-}profile_{Fav}(u_j) = tweets_{Fav}(u_k)\forall k \in followees(u_j) \tag{3}$$

$$read\text{-}profile_{RT}(u_j) = tweets_{RT}(u_k)\forall k \in followees(u_j) \tag{4}$$

In both cases, user profiles comprise terms appearing in each of the considered tweets selected according to several text processing strategies, which are described in Section 4.2. Profiles are represented following the traditional vector space model proposed by Salton et al. (1975), in which each vector dimension corresponds to an individual term weighted by its frequency of appearance.

It is important to highlight that weighting strategies requiring knowledge of the full collection of tweets, such as TF-IDF, cannot be applied. Although the experimental evaluation is performed on a closed set of documents, the approach is intended for performing followee recommendation in a real-time setting. In such setting, posts would be constantly arriving. This has two implications. First, there is no fixed available corpus of documents on which base the computation of the IDF. Second, if the data collection would be considered to expand every time a new tweet is known, the statistics for determining the TF-IDF score of each feature would be periodically computed, which would result in a very inefficient approach. Note that, not only the statistics of the terms in the newly arriving tweet would be computed, but also the IDF statistics of the other terms in the tweet should also be updated. Consequently, although some information regarding the overall relevance of terms might be lost, in highly dynamic environments it is preferable to use more efficient weighting schemes, such as term frequency.

Once user profiles are built, the similarity between two user profiles can be computed using the cosine similarity metric (Salton and McGill, 1983). 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 topological features. Typically, these algorithms compute the similarity between nodes based on their neighbourhoods or ensembles of paths. The usual topological metrics and local similarity indexes applied to *Twitter* follower/followee networks that were included in this study are Common Neighbours, Common Followees, Common Followers and Sørensen Index (Lü and Zhou, 2011). In all of the following definitions, x and y denote nodes, $\Gamma(x)$ denotes the set of neighbours of x, $\Gamma_{out}(x)$ denotes the set of followees of x, $\Gamma_{in}(x)$ denotes the set of followers of x, and k_x is the degree of node x.

Common Neighbours: Measures the overlap of the ego-centric networks of two users, regardless of link direction. This is the ratio between the intersection and the union of each user's followers and followees. It can be formally defined as in the following equation:

$$\frac{|\Gamma(x) \cap \Gamma(y)|}{|\Gamma(x) \cup \Gamma(y)|} \tag{5}$$

Common Followees: Measures the overlap of the followee sets (outgoing links), i.e. to what extent two users follow the same people. The fact that two users have common followees is possibly denoting that both are interested in the same type of information. This metric is an adaptation of the Jaccard similarity measure. It can be formally defined as in the following equation:

$$\frac{|\Gamma_{out}(x) \cap \Gamma_{out}(y)|}{|\Gamma_{out}(x) \cup \Gamma_{out}(y)|} \tag{6}$$

Common Followers: Measures the overlap of the followers sets (incoming links), i.e. to what extend two users are followed by the same people. Users having common followers shared the same audience. It can be formally defined in the following equation:

$$\frac{|\Gamma_{in}(x) \cap \Gamma_{in}(y)|}{|\Gamma_{in}(x) \cup \Gamma_{in}(y)|} \tag{7}$$

Sørensen Index: Measures the number of shared neighbours, but penalises this number using the sum of the neighbourhoods sizes. It can be formally defined as in the following equation:

$$\frac{2|\Gamma(x) \cap \Gamma(y)|}{k_x + k_y} \tag{8}$$

3.3. Personality

Psychology defines personality as a set of emotional, attitudinal and interpersonal processes that are specific to each individual person, and several temperamental and behavioural response patterns (Funder, 2012; Adali and Golbeck, 2012). Consequently, personality can be considered as one of the most important factors influencing human behaviour as it can affect how people react, behave and interact with other individuals. Several authors (Costa and McCrae, 1994, 1997; McCrae and Costa, 1982; Moss and Susman, 1980) have agreed that personality remains stable during adulthood, as it exhibits considerable continuity and consistency over time. Thus, a single assessment can be sufficient to infer the personality of users in the short to medium term. Social environments, both real and virtual, can encourage the manifestation of personality as they satisfy all the basic psychological needs, such as relatedness to other individuals, competence and autonomy (Sherman et al., 2012). Moreover, there is a relation between the personality of individuals and their tastes and interests regarding, for example, affective experience and social behaviour (Cuperman and Ickes, 2009). This implies that individuals with matching personalities might have similar interests.

Several works have aimed at finding a set of features or characteristics to describe personality. Tupes and Christal (1961, 1992) were the first authors who identified five recurrent features in personality. Subsequent works (Noller et al., 1987; McCrae and Costa, 1989) confirmed those findings and offered evidence of the existence of such features. Costa and McCrae (1992) presented a hierarchical model for defining personality as the composition of those five features or dimensions known as Five-Factor or Big Five

Table 1
Big Five personality dimensions.

Agreeableness	Being sympathetic, cooperative and helpful towards others. Tend to be optimistic and to trust other people easily
Extraversion	Being outgoing, friendly, assertive and energetic. Tend to display high degrees of sociability and talkativeness
Openness to Experience	Being curious, intelligent and imaginative. Strong intellectual curiosity, a preference for novelty and variety, and an artistic and sophisticated taste
Conscientiousness	Being organised, persevering, disciplined, achievement-oriented and responsible. Tend to be extremely reliable, high achievers, hard workers and planners
Neuroticism	Being anxious, insecure, moody, and sensitive. This dimension assesses the degree of Emotional Stability, anxiety and impulse control

Table 2
Data collection general statistics.

Total number of seed users	1852
Total number of second-level users (seed users followees)	545,286
Total number of tweets (seed users)	2,307,920
Average number of tweets per user (seed users)	1247
Total number of tweets (second-level users)	1,058,285,978
Average number of tweets per user (second-level users)	1941
Total number of favourite tweets (seed users)	316,419
Average number of favourite tweets per user (seed users)	171
Total number of favourite tweets (second-level users)	213,139,602
Average number of favourite tweets per user (second-level users)	391
Total number of followee relations (seed users)	780,220
Average number of followee relations per user (seed users)	422
Total number of followee relations (second-level users)	1,539,661,626
Average number of followee relations per user (second-level users)	2824

model. The model is acknowledged to define some of the most essential aspects of personality, even though its theoretical foundations have been objected (Waller and Ben-Porath, 1987; Block, 1995). Table 1 summarises the main characteristics of each personality dimension.

In Selfhout et al. (2010) and Cuperman and Ickes (2009) the influence of the Big Five personality dimensions on the friendship selection process was studied. Both studies concluded that the different Big Five 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 Conscientiousness were associated with a higher number of reciprocal friends. Although Extraversion resulted in the most important factor for selecting friends, Agreeableness attracted more individuals than Extraversion. Neither Conscientiousness or Neuroticism showed evidence of actual similarity among friends. Finally, whereas Openness to Experience is more interested in interacting with new friends, Neuroticism is more interested in maintaining relationships.

Generally, to accurately assess personality, individuals are required to explicitly answer a personality questionnaire. However, such tests are impractical to perform personality analysis in the context of social media. Gottschalk and Gleser (1969) and Rosenberg and Tucker (1979) among others have provided evidence suggesting that people's mental states and personality can be predicted by the words they use. In this regard, several works (Bai et al., 2012; Mairesse et al., 2007; Adali and Golbeck, 2012; Golbeck et al., 2011) have cast the problem of determining personality as a classification or regression problem over directly observable information, such as text, conversations, conversational transcripts or even posts in social networks. These approaches allow to efficiently assess user personality in the context of online and massive systems. Particularly, Mairesse et al. (2007) based their personality assessment tool on the Linguistic Inquiry Word Count (LIWC) features (Pennebaker et al., 2003, 2007), and the 14 Medical Research Council (MRC) Psycholinguistic features (Coltheart, 1981), both including syntactic and semantic information. Experimental evaluation of the Personality Recogniser application developed by these authors was based on two datasets. First, a dataset comprising 2479 essays written by psychology students, who were told to write whatever came into their mind for 20 min. Second, a dataset comprising conversational extracts. The tool obtained the best prediction results for the Openness to Experience dimension, whereas it obtained the worst results for the Extraversion and Conscientiousness dimensions. Results seemed to indicate that simple algorithms such as Naïve Bayes or regression trees tended to perform better than more complex algorithms for textual data. On the contrary, complex algorithms, such as support vector machine (SVM), tended to perform better for conversational data and big-data corpora.

4. Data collection and processing

For assessing the impact of personality in the accurate prediction of followees, a *Twitter* dataset was created by crawling a set of 1852 seed users extracted from De Choudhury et al. (2010). Table 2 summarises the general statistics of the resulting data collection.

In order to obtain meaningful profiles for content analysis, every selected seed user had to list the language account as English, tweets written in English and had at least 10 followees and 10 published tweets. For determining whether tweets were written in English, the first 200 downloaded tweets of each user (or less, depending on the total number of published tweets) were analysed. The language detection was based on a Java version of TextCat[4], which implements the algorithm presented in Cavnar and Trenkle (1994). As a big quantity of text was given as input to the language detection tool, results were expected to be accurate. Thus, only those users whose tweets were detected as English as the top-1 language were selected.

For those users, user account information, all tweets, favourite tweets, followees and followers were retrieved from *Twitter*. The same data was retrieved for all the followees of the seed users. All the information was obtained through the Twitter API[5]. The content of tweets was first used to detect the personality traits of users (Section 4.1), and then processed to build the different content-based profiles (Section 4.2).

4.1. Personality profiles

The personality traits corresponding to each user were automatically computed by means of the models and tool developed by

[4] http://odur.let.rug.nl/vannoord/TextCat/
[5] https://api.twitter.com

Mairesse et al. (2007). In order to compute personality profiles, the full content of tweets was considered, i.e. no pre-processing step was applied to the text of tweets. Particularly, as the tool considers the LIWC features, all terms are important for defining the usage patterns of each part-of-speech. Moreover, adjectives and adverbs are of particular importance as they can convey highly important information regarding personality.

The tool was modified to compute the scores corresponding to several users in parallel, and to reduce the memory consumption and computing times by introducing less resource demanding structures. Finally, the computation of the features for predicting personality was separated from the actual computation of the personality scores. SMOreg (Shevade et al., 2000), an implementation of Support Vector Machines (SVMs) for regression, was the selected model for computing personality scores as it was reported to obtain the most accurate results for conversational and big data corpora (Mairesse et al., 2007).

4.2. Content profiles

Unlike when computing the personality profiles in which every term appearing in tweets was considered, terms in content profiles were filtered according to two text processing approaches. The first one considered the full-text of tweets (named *FULL*), whereas the second one applied pre-processing steps to tweets (named *PROC*). For the second approach, the collected tweets were lexically and syntactically pre-processed. Although the selected user accounts were determined to mostly post in English, as the language detection approach relies on joint statistics, it cannot be guaranteed that all of a user tweets were written in English. In order to guarantee uniformity in the language of the analysed tweets, a further language analysis step was applied to each individual tweet. This step aimed at removing tweets written in languages very different to English. It is important to highlight that the language detection algorithm does not have a perfect accuracy, possible failings include a list with several languages or no language at all. Furthermore, the algorithm was reported to improve its precision as the quantity of supplied text increased. As in this case, only 140 characters were given as input, the tool had a higher probability of misclassifying tweets by confusing languages with similar N-gram distribution. Considering those situations, to avoid having false negatives (i.e. tweets marked as non-English that were actually English), if English was not included in the top 3 of languages selected by the algorithm, the tweet was classified as a non-English one and discarded.

Second, a probabilistic Part of Speech (POS) tagging was performed based on the tool defined by Gimpel et al. (2011)[6], which was specifically designed for tagging social content and reported an accuracy of 90%. The tool recognises and classifies tokens in 24 categories such as nouns, proper nouns, verbs, adjectives, adverbs, numbers and punctuation marks. For the purpose of this work, only those tokens labelled as nouns or verbs were selected, whereas the other tokens were discarded. The remaining text was processed in order to remove stop-words. The stop-word list proposed by Lewis et al. (2004) in combination with the stop-words defined in the MySQL Manual[7] were used. Finally, in order to reduce the syntactic variations of terms and improve the probability of finding similarities between profiles, the Porter Stemmer algorithm (Porter, 1997) was used.

[6] http://www.ark.cs.cmu.edu/TweetNLP

[7] dev.mysql.com/doc/refman/5.7/en/fulltext-stopwords.html

5. Quantitative evaluation of matching personalities

The empirical study presented in this paper aims at analysing how user personality can condition the selection of followees by combining personality traits with the most commonly used factors in followee recommendation systems (topology and content). Such combination of factors is inserted into a recommendation algorithm that computes the similarity among a target user and each potential followee to recommend. Then, the algorithm ranks those potential followees in decreasing order of similarity. To assess the personality matching between two users, the scores corresponding to each of the five dimensions in the Big Five model must be comparable, i.e. they have to be summarised into one unique personality matching score.

Most of the approaches presented in the literature (Tkalcic et al., 2009; Hu and Pu, 2011) analysed personality by considering the overall similarity score between users using the cosine similarity among all dimensions. However, in a previous study over a large sample of *Twitter* users (Tommasel et al., 2015) it was shown that this measure might result inadequate for computing the personality matching between two users, as it is highly influenced by the score of a single dimension, regardless of the score of the remaining ones. Consequently, the overall personality similarity based on vector distance might not accurately assess the actual similarity between users across the individual personality dimensions. Instead, the previous study showed the existence of several patterns of followee selection with certain personality characteristics when considering both a dimension-to-dimension and a cross-dimension analysis. These findings support those of Selfhout et al. (2010), who stated that the effect of each personality dimension on friendship relations is higher and more important than the overall effect of the five dimensions considered as a whole. Due to such reason, several strategies for establishing the personality similarity score between two users, i.e. the matching degree of the personalities, were defined for this study. The strategies consider both the statistical distribution of personality scores across the five separate dimensions, as well as several relations among individuals exhibiting certain personality scores found in the literature.

Each strategy consists of a set of matching rules, one for each of the five personality dimensions, which produce a similarity score in the $[0, 1]$ range. Each rule models the compatibility of two users in terms of a certain personality dimension. For example, a rule for the Extraversion dimension would assign a matching score of 1 to a user and a potential followee if both personality 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 dimension scores. It is important to highlight that the rules corresponding to the Conscientiousness and Emotional Stability dimensions do not consider the relations among individuals exhibiting certain scores as neither Selfhout et al. (2009) nor Cuperman and Ickes (2009) reported significant effects of any of those dimensions on the friendship selection processes.

Eq. (9) shows the general form of the overall personality matching score between a user (u) and a potential followee (pf), as an average (μ) of the *matchingScore* computed for each personality dimension (*dimension*). Then, each strategy defines a particular form for computing the *matchingScore* function:

$$over\ all\ Personality\ Matching(u, pf) \\ = \mu\left(\sum matching\ Score(u, pf, dimension)\right) \tag{9}$$

Naïve strategy: For this strategy, each rule analyses the personality score of the potential followees in relation to the statistical distribution of personality scores of the actual user followees.

The rationale behind this strategy is that, if the user tends 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.

It is important to consider the characteristics of the possible statistic measures to be used. Average measures of data, as the median and the mean, represent typical and exact values for a dataset, i.e. they do not give any indication regarding the actual data distribution or dispersion, or the presence of data outliers. As a result, the extent to which the median and mean are good representatives (or estimators) of the values in the dataset depends upon the variability or dispersion in the original data. Thus, a measure that is not influenced by outliers, i.e. a robust measure, is needed. The most commonly used robust statistic is the interquartile range. It is worth noting that robust estimators typically are less efficient when compared to conventional estimators for data that is drawn from a distribution without outliers (for example a normal distribution). However, these estimators are more efficient for data that is drawn from a mixture or unknown distribution for which non-robust statistics should not be used. Finally, as robust estimators are not based on the supposition of a symmetric distribution of data, they are not as influenced by data outliers as the mean is. Consequently, the interquartile range arises an adequate and robust statistic when considering skew data, or when the exact data characteristics are not known in advance, as in highly dynamic domains, when new data instances arrive continually.

The interquartile range indicates the range over which the central 50% of values within the dataset are dispersed. It is found by subtracting the lower quartile (i.e. the middle value between the smallest number and the median of the data distribution) from the upper quartile (i.e. the middle value between the median and the highest value of the data distribution). Then, this strategy rewards those followees whose score is contained in the central 50% of the score distribution. For each rule, the highest matching score is achieved when the personality score of the potential followee is contained in the interquartile range. Otherwise, the matching score is zero. No relations among individuals exhibiting certain personality scores are considered for these rules.

Eq. (10) shows the rule for computing the *matchingScore* for each dimension according to this strategy. The *interquartilAgreement*$_{NAIVE}$ is defined as in Eq. (11), where *score* represents the personality score of *pf* in the specific personality *dimension*, and *interquartile.range* represents the range of score preferences of the user *u* regarding the specific personality *dimension*:

$$matchingScore(u, pf, dimension) = interquartilAgreement_{NAIVE}(u, pf, dimension) \quad (10)$$

$$interquartilAgreement_{NAIVE}(u, pf, dimension) = \begin{cases} 1 & score(pf, dimension) \in interquartile.range(u, dimension) \\ 0 & every\ other\ case \end{cases} \quad (11)$$

Boosted agreeableness and extraversion strategy (AE): For this strategy, the rules corresponding to the Agreeableness and Extraversion dimensions are modified in order to consider the relations among individuals with certain scores in those dimensions as identified in Selfhout et al. (2010) and Cuperman and Ickes (2009). Ultimately, the matching would prioritise the relation between users showing a natural tendency of becoming friends, as shown in Selfhout et al. (2010) and Cuperman and Ickes (2009).

The rules for the Openness to Experience, Conscientiousness and Emotional Stability dimensions are computed as in the Naïve Strategy. For computing the matching score for the Agreeableness and Extraversion dimensions, the rules (as shown in Eq. (12)) divide the score into two parts: half is computed according to the quartile distribution (the *interquartilAgreement*$_{BOOSTED}$ as in the Naïve Strategy), and the remaining half (*scoreAgreement*) is assigned according to the relation between the scores of both the user and the potential followee. The *interquartilAgreement*$_{BOOSTED}$ is now defined as Eq. (13) shows. The definition of the

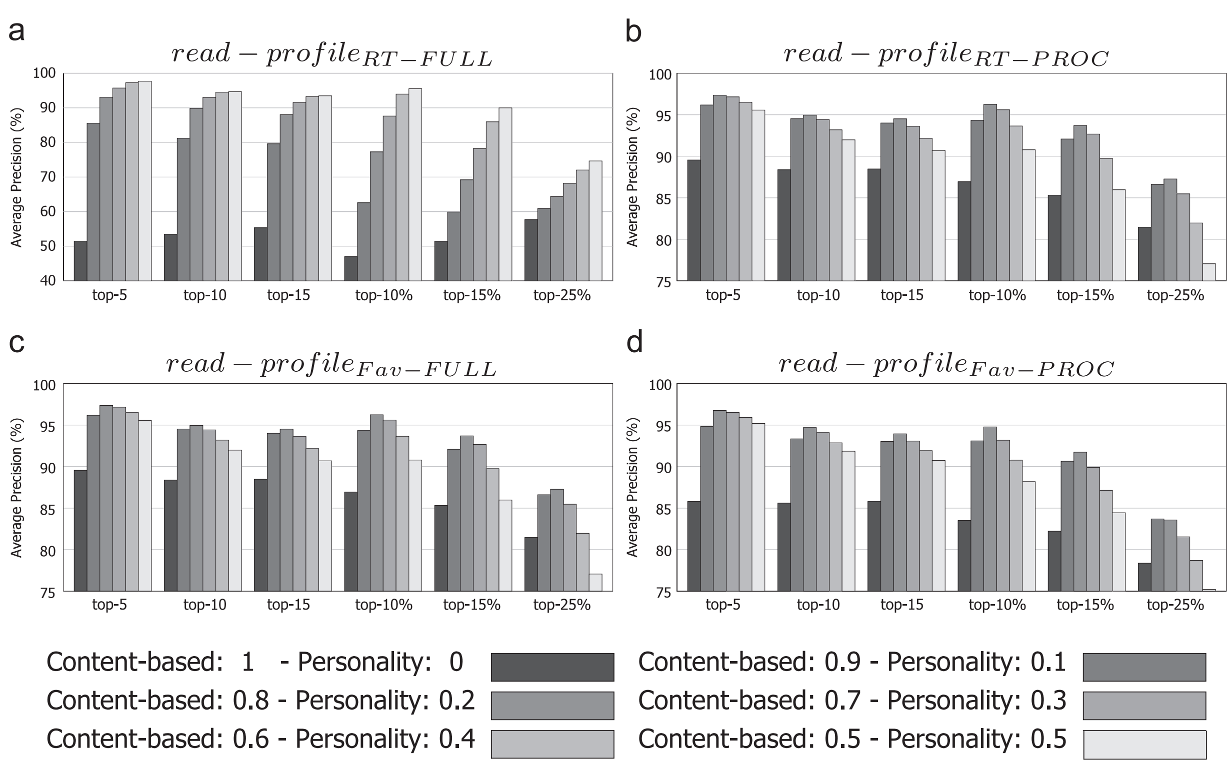

Fig. 1. Average precision of content-based followee recommendation using the Naïve strategy for quantitative analysis of personality.

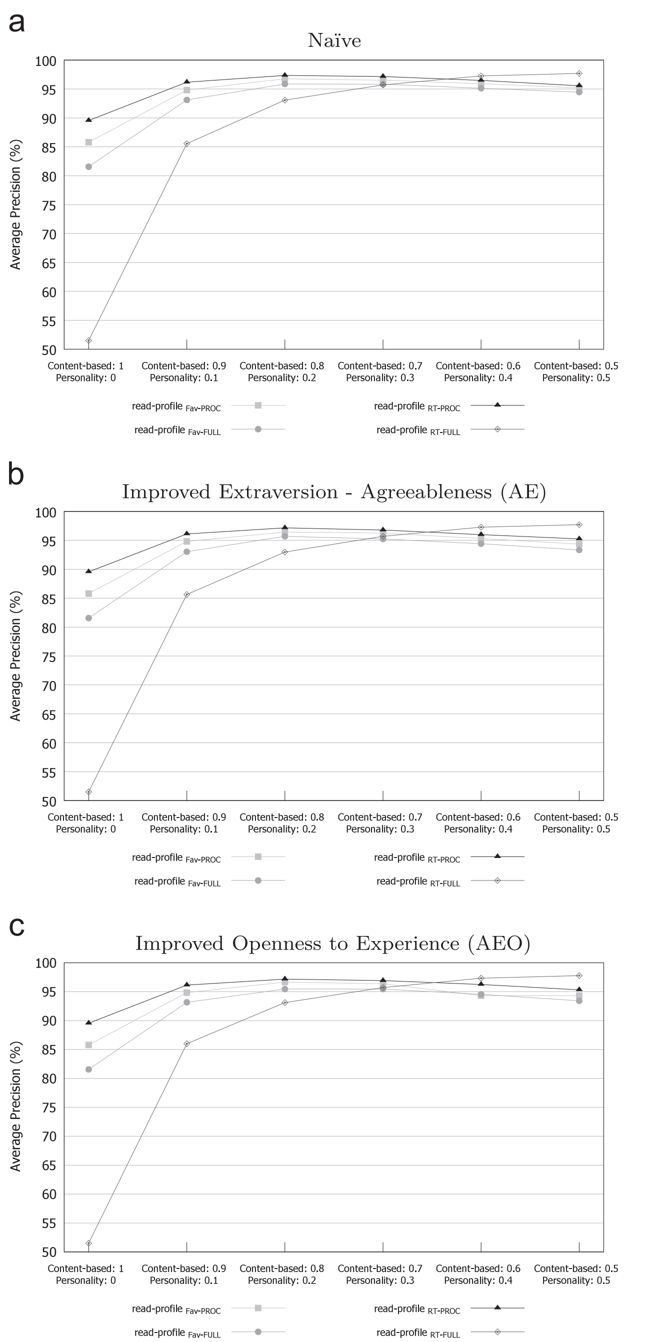

Fig. 2. Average precision at top-5 of content-based followee recommendation for the three strategies of quantitative analysis of personality.

scoreAgreeement is particular to each of the boosted dimensions:

$$matchingScore(u, pf, dimension) = interquartilAgreement_{BOOSTED}(u, pf, dimension) + scoreAgreement(u, pf, dimension) \quad (12)$$

$$\text{interquartilAgreement}_{\text{BOOSTED}}(u, \text{pf}, \text{dimension}) = \begin{cases} 0.5 & \text{score}(\text{pf}, \text{dimension}) \in \text{interquartile.range}(u, \text{dimension}) \\ 0 & \text{every other case} \end{cases} \quad (13)$$

In the case of the Extraversion dimension, Cuperman and Ickes (2009) found that the best and most rewarding relationships involve individuals with similar personality scores, rather than dissimilar ones. As a result, the rule (as shown in Eq. (14)) assigns a score of 0.5 if both individuals are extroverted, i.e. have high personality scores in the dimension, or 0.25 if both individuals are introverted, i.e. have low personality scores in the dimension. No score is assigned if one individual is extroverted and the other introverted:

$$\text{scoreAgreement}(u, \text{pf}, \text{Extraversion}) = \begin{cases} 0.5 & \text{both } u \text{ and pf are Extroverted} \\ 0.25 & \text{both } u \text{ and pf are Introverted} \\ 0 & \text{one Extroverted and other Introverted} \end{cases} \quad (14)$$

In the case of the Agreeableness dimension, Cuperman and Ickes (2009) found that the best and most rewarding relationships involved agreeable individuals, whereas the least rewarding relationships involve disagreeables individuals. However, relations involving both an agreeable and a disagreeable individuals are also desirable. As a result, the matching rule (as shown in Eq. (15)) assigns a score of 0.5 if both individuals are agreeable, i.e. have high personality scores in the dimension, or 0.25 if either of the individuals is agreeable. No score is assigned if both individuals are disagreeable:

$$\text{scoreAgreement}(u, \text{pf}, \text{Agreeableness}) = \begin{cases} 0.5 & \text{both } u \text{ and pf are Agreeable} \\ 0.25 & \text{either } u \text{ or pf is Agreeable} \\ 0 & \text{none is Agreeable} \end{cases} \quad (15)$$

Boosted openness to experience strategy (*AEO*): This strategy only modifies the rule corresponding to the Openness to Experience dimension. The rules for the other dimensions are computed as in the previous strategy, so that the Agreeableness, Extraversion and Openness to Experience dimensions are boosted. Selfhout et al. (2010) found that the Openness to Experience dimension predicted the possibility of being selected as a friend. Moreover, Cuperman and Ickes (2009) found that individuals who are open to new experiences, i.e. have high scores in such dimension, are interested in interacting with new friends. As a result, the rule (as shown in Eq. (16)) assigns a score of 0.5 according to the quartile distribution, and 0.5 if both individuals are open to new experiences or 0.25 if either of the individuals is open to new experiences. No score is assigned if none of the individuals is open to new experiences.

$$\text{scoreAgreement}(u, \text{pf}, \text{Opennes to Experience}) = \begin{cases} 0.5 & \text{both } u \text{ and pf are Open to Experience} \\ 0.25 & \text{either } u \text{ or pf is Open to Experience} \\ 0 & \text{none is Open to Experience} \end{cases} \quad (16)$$

6. Assessing the impact of personality in followee recommendation

As the goal of this study is to analyse how the selection of followees is affected by each individual's psychological characteristics, the recommendation algorithm needs to combine the topological and/or content-based factors with the matching personality scores of each pair of users. Consequently, the similarity between a user and a potential followee must be unified into a unique similarity score in order to obtain a personalised similarity ranked list of suggested followees. In this work, the different analysed factors for followee recommendation were linearly combined as it is one of the simplest and most effective methods for combining multiple scores (Gerani et al., 2012; Wu, 2012). Such combination also offers certain flexibility as different weights can be assigned to the individual factors in order to improve the final one. Moreover, weighting factors differently allow to determine to what extent personality impacts on each of them.

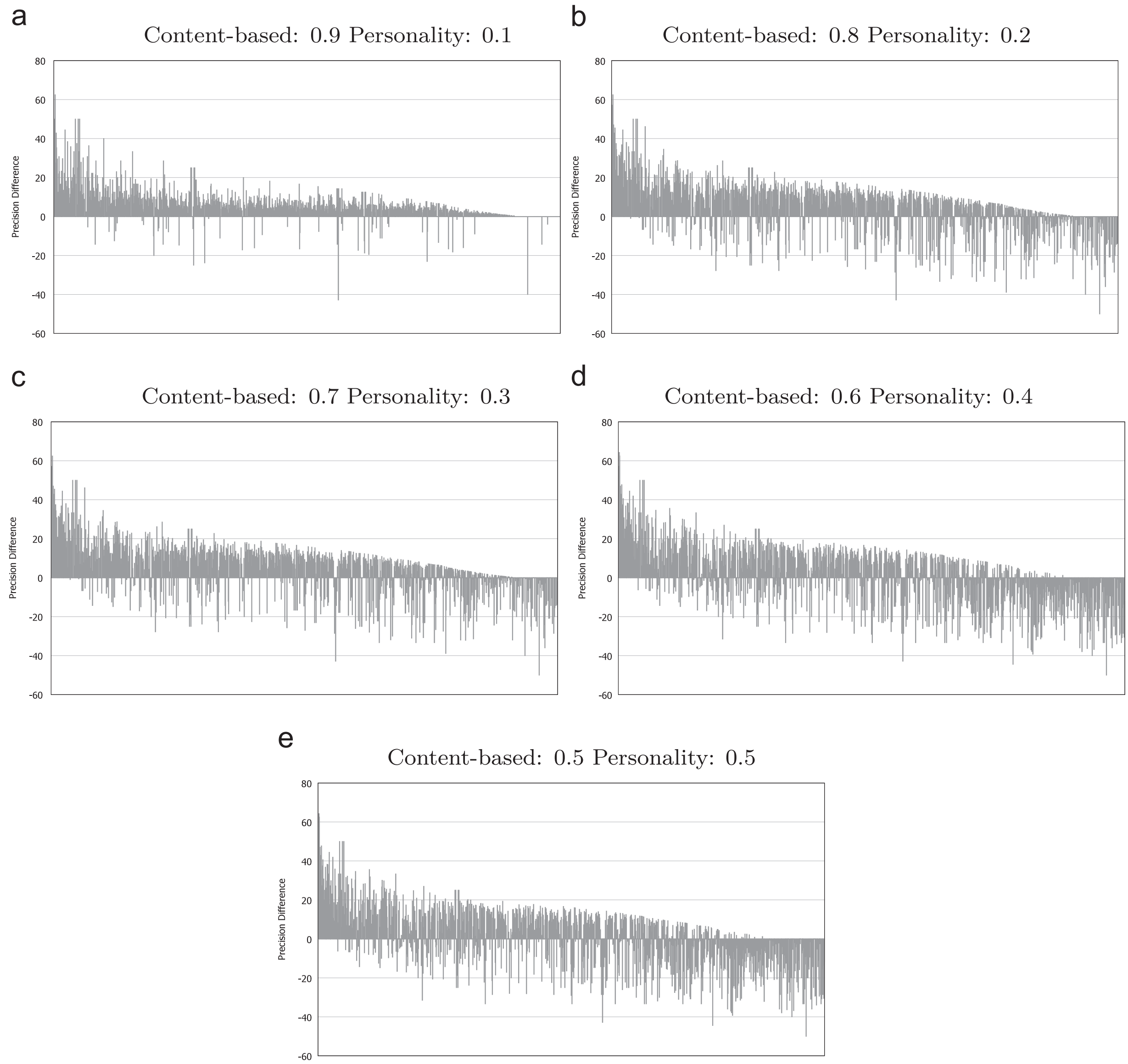

Fig. 3. Precision differences at top-25% for several weight combinations of personality and content (*read-profile*$_{RT\text{-}PROC}$).

The methodology for testing the generated recommendations can be described as follows. 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 possible followees from this pool by selecting the best ranked users, and the evaluation measures if the actual followees are recommended. In other words, the evaluation determines whether the algorithm was capable of identifying those users who were already considered interesting.

The quality of recommendations was evaluated by selecting the top-*N* recommended users and computing the overall precision. In this context, precision can be defined as the percentage of relevant recommendations (i.e. the number of actual followees that was discovered by the algorithm) regarding the total number of recommendations. For evaluating link prediction problems in social networks (e.g. followee recommendation), only positive examples are available (i.e. the actual user followees) as social sites do not allow to explicitly specify negative relationships. Hence, the lack of links between two users is considered as an implicit indication that the first user is not interested in following a second user. However, such lack of relationships could be because either user is not interested in receiving the other user tweets or simply because he/she has not yet discovered the other user in the *Twitter* network. In the latter case, the recommendation is also appropriate and will be valuable for the user but it would be still counted as an incorrect one in the precision and hit-rate metrics computation. This, in turn, leads to an underestimated assessment of precision. As the evaluation only considers the actual followees of the user, instead of asking the user whether the recommended users are interesting, the reported precision represents the worst-case scenario precision. In other words, this is not a thread to the validity of the experiments as any other recommended followee, in which the user might show interest in, would only increase the precision of the recommendation algorithm. For all the experimental evaluations, *N* was set to 5, 10, 15, and 10%, 15% and 25% of the ranked list of recommendations. The overall performance of the algorithm was computed as the aggregation of the scores of the multiple seed users for each list of length *N*.

6.1. Impact of personality on content-based followee recommendation

The effect of adding personality as a factor in content-based followee recommendation (Section 3.1) is shown in Fig. 1(a)–(d).

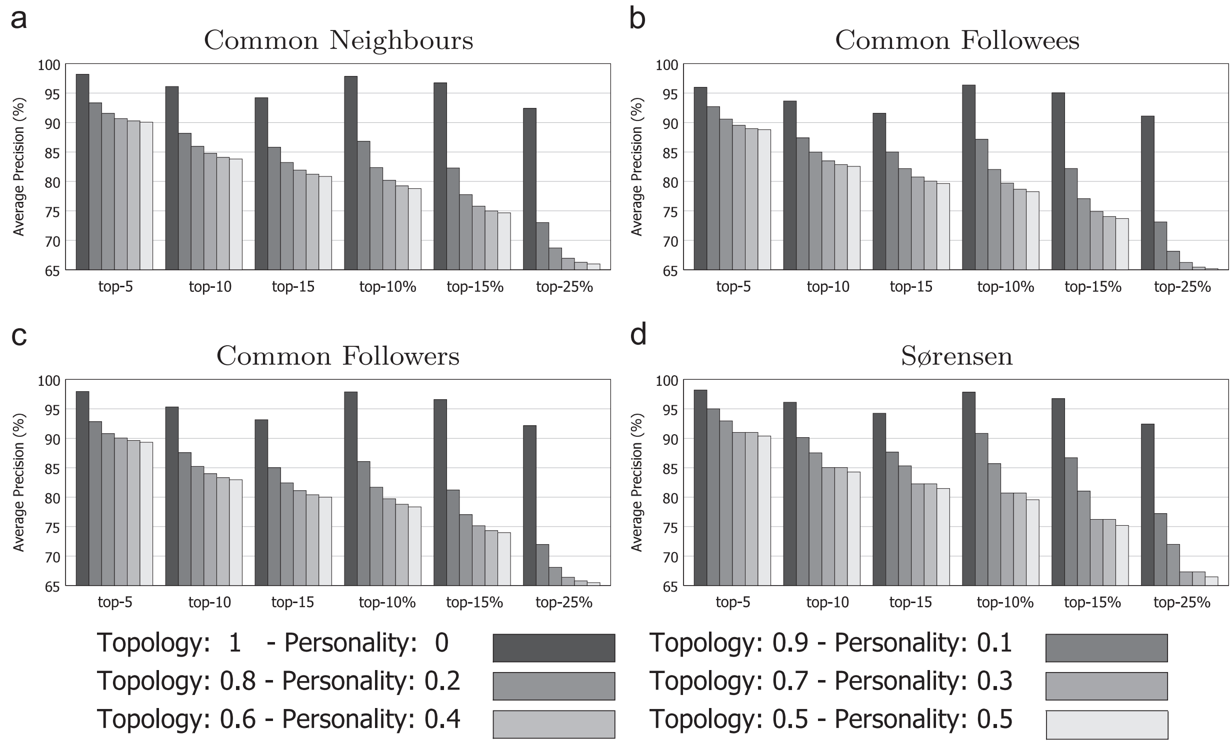

Fig. 4. Average precision of topology-based followee recommendation using the Naïve strategy for quantitative analysis of personality.

Each figure summarises the average precision for each of the predefined *N*, including results for six linear combinations of factor's weights, when considering the Naïve strategy for analysing personality.

As it can be observed, adding a quantitative analysis of personality had a positive impact on the recommendation precision for all the proposed *reading profile*s. In the content-based setting, *reading profiles* of seed users are compared against *publishing profiles* of the potential followees. In all cases, increasing the personality weight improved precision results of followee recommendation.

For most of the *reading profiles*, maximum precision was achieved when considering a personality weight of 0.2. Furthermore, the combination of personality and content-based factors achieved its maximum precision improvements regarding the individual content-based factors when selecting the top-5 recommended followees. As a result, it can be stated that considering a quantitative analysis of personality in combination with content-based factors could help to correctly place the most important or interesting users in the first positions of the ranking of suggested users.

Considering the previous results, Fig. 2 summarises recommendation precision when selecting the top-5 recommended followees for each strategy of personality analysis. As the figure shows, the different strategies seem to achieve similar precision results. However, the results of the AEO strategy are slightly better than those obtained when considering the AE or the Naïve strategy with differences up to a 2% for the top-5 recommended users. These results could imply that although adding information regarding relations among specific personality dimensions improves precision, such improvements are not significant, so that, the Naïve strategy could be effectively applied to improve the quality of recommendations.

Fig. 3 shows precision results per user when considering the *read-profile*$_{RT\text{-}PROC}$ using the Naïve strategy, for each of the evaluated linear combination of weights. In this case, the results for the largest top-*N* recommended followees are reported, i.e. top-25%. For each user the difference in precision between the recommendations based exclusively on content-based factors and recommendations achieved when adding personality was computed. Each figure shows the seed users sorted in ascending order according to the precision achieved when only considering the content-based factor (plotted in the *X*-axis) for the different personality weights. 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 seen, considering 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 could imply that personality is an important factor to consider for recommending potential followees. Furthermore, these results impose a limit to the weight that can be assigned to personality in order to improve results, as assigning weights higher to such limit could decrease the precision of recommendations.

As regards the remaining *reading profiles*, adding personality resulted in a continuous precision improvement when its weight was lower than 0.2. On the contrary, when personality weights were higher, precision results tended to stabilise and then decrease, achieving their minimum values when considering personality and the content-based factor with equal weights. It is worth noting that, although precision decreased as the importance of personality increased (up to a maximum weight of 0.4), results were still higher than when recommending solely based on the content-based factor. In summary, content-based followee recommendation can be improved when combined with a quantitative analysis of personality.

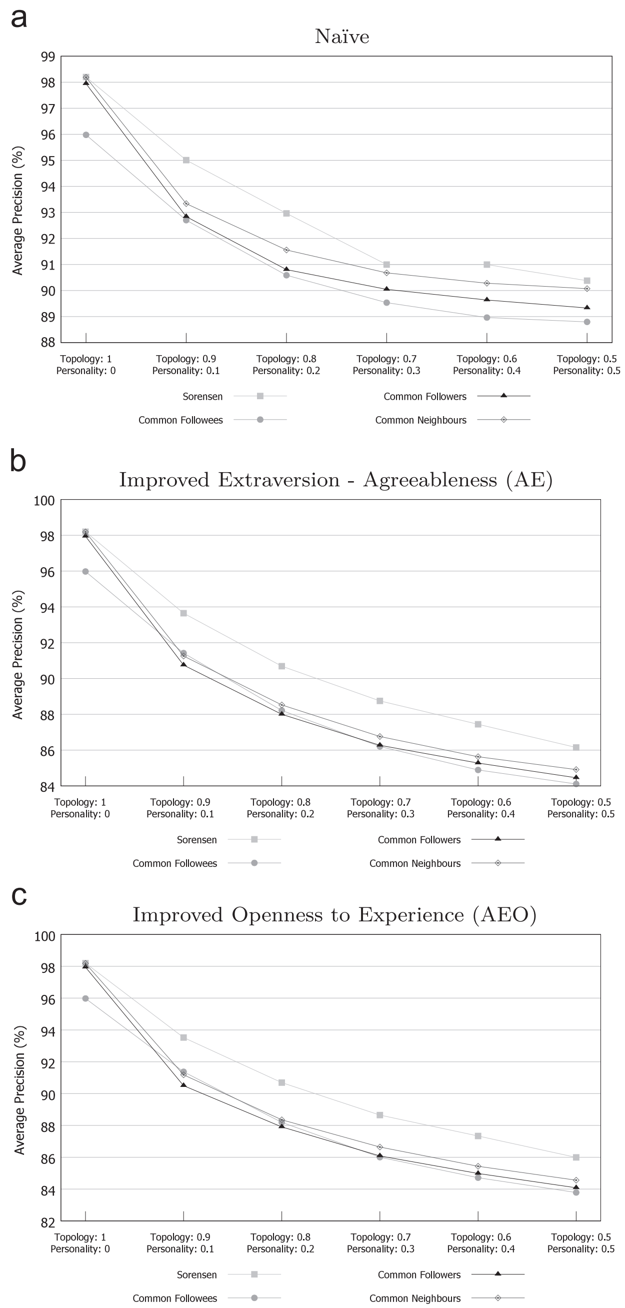

Fig. 5. Average precision at top-5 of topology-based followee recommendation for the three strategies of quantitative analysis of personality.

6.2. Impact of personality on topological followee recommendation

The effect of adding personality as a factor in topology-based followee recommendation (Section 3.2) is shown in Fig. 4(a)–(d). Each figure summarises the average precision for each of the predefined *N* when considering the Naïve strategy and the results for six linear combination of factor's weights.

As the figures show, adding a quantitative analysis of personality had a negative impact on the recommendation precision for all the proposed topological metrics. In all cases, adding personality decreased the precision achieved when considering only the topology factors. These results imply that, although personality seemed to be an important factor for followee recommendation when added to content-based factors, it did not have the same effect with respect to topological factors. Alike the previous case, the combination of topological factors and personality achieved maximum precision when considering low personality weights, i.e. 0.1.

Fig. 5 summarises recommendation precision when selecting the top-5 recommended followees for each quantitative personality analysis strategy. Unlike when applied to the content-based factors, the Naïve strategy for quantitatively analysing personality achieved better precision results than both the AE and the AEO strategies, with differences reaching a 6.11%. These results could imply that when combined with topological factors, considering relations among specific personality dimensions does not lead to further improvements. Regarding both AE and AEO, as the precision differences were lower than 0.44% it is not possible to establish the superiority of one over the other. It can be stated that the Openness to Experience dimension did not provide any useful information to trigger a significant precision improvement. Consequently, the Naïve strategy resulted in the highest results when compared to both the AE and AEO strategies. In summary, these results reinforce the superiority of the statistically based strategy for quantitatively analysing personality over those strategies that also consider the specific relations among personality dimensions.

Fig. 6 shows precision results per user regarding the Naïve strategy and the topology metric that achieved the best precision results when combined with personality (i.e. Sørensen Index) for each of the evaluated linear combinations of weights. In this case, the results for the largest top-*N* recommended followees are reported, i.e. top-25%. As for the content-based factors, each figure shows the seed users sorted according to the precision achieved when only considering the topology factor (plotted in the *X*-axis).

Unlike when considering the content-based factors, combining topology and personality did not lead to precision improvements for the majority of users. However, there was a small proportion of users for which combining topological factors and personality resulted in precision improvements. 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. As well as when considering the content-based factors, as the personality weight increased the differences tended to worsen. For those differences above zero, however, increasing the personality weight did not cause a detriment of precision. 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.

As regards the remaining topology factors, adding personality led to lower precision results than those of the Sørensen Index. In all cases, adding personality incurred in further reductions of recommendation precision. The worst results were obtained for the Common Followees similarity metric. In summary, topology-based followee recommendation is not improved when combined with a quantitative analysis of personality, excepting when the similarity only based on topological factors is lower than a threshold, which in the analysed data was 0.66 of topological similarity.

6.3. Statistical significance of results

The statistical significance of precision results was evaluated according to the definitions and methods proposed by Corder and Foreman (2009). For each combination of followee recommendation factors, the statistical significance of their precision results was tested in order to determine whether results differences are significant and not due to a random or sampling error. The normality of precision result samples was evaluated by analysing their skewness, kurtosis, and performing both the Shapiro and the Anderson–Darling tests. As the normality tests failed for at least one result sample, statistical significance of results had to be

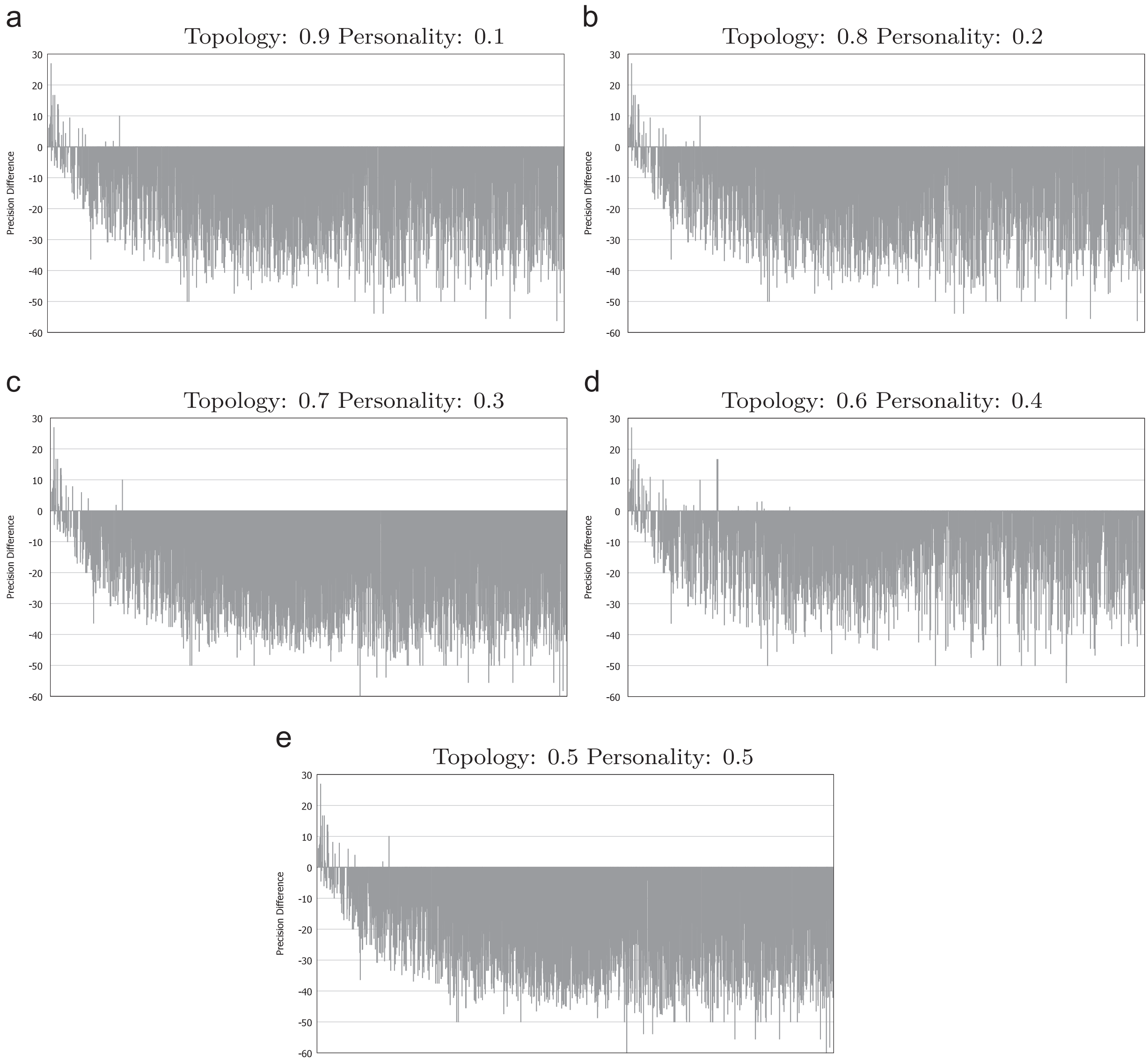

Fig. 6. Precision differences at top-25% for several Weight combinations of personality and topology (Sørensen).

Table 3
Friedman test results (degrees of freedom: 5 – critical value: 15.09).

Followee Recommendation Factors	*Statistic value*	*Significance level*
read-profile$_{RT\text{-}FULL}$	5721.128	$< 2.2e-16$
read-profile$_{RT\text{-}PROC}$	1726.086	$< 2.2e-16$
read-profile$_{Fav\text{-}FULL}$	1718.651	$< 2.2e-16$
read-profile$_{Fav\text{-}PROC}$	507.919	$< 2.2e-16$
Common Neighbours	6357.037	$< 2.2e-16$
Common Followees	6029.059	$< 2.2e-16$
Common Followers	5142.998	$< 2.2e-16$
Sørensen	6613.550	$< 2.2e-16$

Table 4
Wilcoxon test results – significance levels at which the null hypothesis can be rejected.

Followee Recommendation Factors	*Significance level*
read-profile$_{RT\text{-}FULL}$	$< 2.2e-16$
read-profile$_{RT\text{-}PROC}$	$< 2.2e-16$
read-profile$_{Fav\text{-}FULL}$	$< 2.2e-16$
read-profile$_{Fav\text{-}PROC}$	$4.108e-11$
Common Neighbours	$< 2.2e-16$
Common Followees	$< 2.2e-16$
Common Followers	$< 2.2e-16$
Sørensen	$< 2.2e-16$

evaluated by means of non-parametric tests. Considering that the precision results for each of the factors combinations were obtained for the same set of seed users, statistical tests for comparing related samples were used, setting the confidence value (*p*-value) to 0.01. To perform the statistical significance tests, two hypotheses were defined: the null and the alternative hypothesis. The null hypothesis stated that no difference existed among the precision results, i.e. adding personality to the followee recommendation algorithm had no significant impact on its precision. On the contrary, the alternative hypothesis stated that adding personality to the followee recommendation algorithm had a significant and non-incidental impact on its precision.

The Friedman test was applied to compare the results of all the five linear combination of factors evaluated for each of the analysed topology and content-based factors. For all the evaluated combinations of factors (shown in Table 3), the Friedman test led to significant results, i.e. the obtained values were higher than the corresponding critical value. As a result, the test established the significant and non-incidental impact of personality on the recommendation precision. However, the Friedman test deemed results as significant if at least one sample is different from the other, and thus it does not indicate how many differences occur or among which samples such difference or differences occur.

To identify the particular differences between pairs of result samples, the Wilcoxon paired test was applied. For each of the factors for followee recommendation combinations, the precision results obtained when only considering the topological or the content-based factor was compared to each of the other evaluated linear combinations. For most tests, the null hypotheses were rejected, suggesting that personality had a significant impact on the recommendation algorithm. Particularly, Table 4 shows the significance levels of the Wilcoxon paired test at which the null hypothesis can be rejected for the best weighting combination of features (0.2 assigned to personality, and 0.8 assigned to content-based or topology factors). As the table shows, when considering the best combination of weights, the null hypothesis can be always rejected. These results imply that considering personality for followee recommendation had a significant and non-incidental effect on results regarding the precision achieved when recommending followees solely based on topological or content-based factors.

7. Conclusions

The continuously increasing number of active users in micro-blogging communities reinforces the necessity of accurately describing users' interests and characteristics in order to overcome the overload of information and help users in finding other interesting users worth following. Hence, new criteria for searching and ranking candidate users have to de devised. Particularly, new ways to accurately capture the real nature of users have to be analysed. Traditionally, most recommendation systems proposed in the literature have solely relied on topological, textual analysis or other individual factors, disregarding the effect of psychological characteristics, such as personality, over the followee selection process.

This study analysed how user personality conditions the followee selection process by combining a quantitative analysis of personality traits with the most commonly used predictive factors for followee recommendation, i.e. topology and content. The combined factors were inserted into a recommendation algorithm that computed the similarity among target users and potential followees, and then ranked those potential followees in decreasing order of importance. Regarding the content-based factors, results showed that adding a quantitative analysis of personality had a positive impact on the recommendation precision for all the proposed content-derived profiles. In all cases, combining personality with content-based factors improved precision results of followee recommendation exclusively based on content. Furthermore, adding personality resulted in a continuous precision improvement up to the point that personality is not longer influential. For higher personality weights, precision results tended to stabilise and then decrease, achieving their minimum values when both personality and content were considered equally important. Even though precision decreased as the importance of personality increased, results were still higher than when recommending solely based on the content-based factor. On the contrary, the combination of personality and topological factors did not lead to precision improvements for the majority of users. However, adding personality resulted in high precision improvements for all the analysed linear combination of weights when the precision achieve solely based on topology factors was reduced. Alike for the content-based factors, as the personality weight increased the differences tended to worsen. For those differences above zero, however, increasing the personality weight did not cause a detriment of precision.

The empirical evaluation showed that personality should be considered as a distinctive factor in the process of followee selection. An accurate appreciation of commonly used factors tied to a quantitative analysis of personality resulted crucial to enhance recommendations only based on such factors. Furthermore, this work presented guidelines regarding how to insert personality into a recommendation algorithm, establishing the circumstances under which adding personality can enhance followee recommendation. Finally, results showed the existence of a limit to the importance that should be assigned to personality in relation with other factors in order to either improve precision results or at least to avoid their reduction. Particularly, content-based followee recommendation was improved when combined with a quantitative analysis of personality, whereas topology-based followee recommendation was only improved given certain conditions (the similarity based only on topological factors was lower than a certain threshold).

Finally, according to Goel et al. (2015), the quality of user recommendation systems in micro-blogging sites has a direct impact on the growth and quality of user engagement. For example, the who-to-follow service in *Twitter* accounts for over the 13% of the connections in the *Twitter* network, without considering the fact that *Twitter* is a viral network in which any new connection could result in additional discoveries and thus new social connections. Moreover, the who-to-follow service has also contributed to *Twitter*'s revenue success. In addition, more than the 15% of *Twitter* users accept a recommendation of the who-to-follow service at least once a month. Consequently, enhancing the quality of recommendations not only increments the quality of social relations and user satisfaction, but also helps to the expansion and revenue of the micro-blogging site. In this regard, the results and guidelines referring to how to leverage on the personality of users could be used to further improve the quality of recommendations. In fact, the presented approach could be deployed as part of any recommendation application already in place in *Twitter* (for example the who-to-follow service) or other micro-blogging sites (such as *Sina Weibo*), could be deployed as a stand-alone Web service or even as a *Twitter* application. The application would have to mine the network topology of those users seeking for users recommendations. Also, it would have to retrieve the published content in order to build both the personality and content-based profiles. Then, recommendations could be made to the user considering his/her personality and the personality of the users to be suggested.

Acknowledgements

This work has been partially funded by ANPCyT (Argentina) under Project PICT-2011-0366 and by CONICET (Argentina) under Project PIP no. 112-201201-00185.

References

Adali, S., Golbeck, J., 2012. Predicting personality with social behavior. In: IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), Istanbul, Turkey, pp. 302–309.

Bai, S., Zhu, T., Cheng, L., 2012. Big-five personality prediction based on user behaviors at social network sites, CoRR abs/1204.4809.

Block, J., 1995. A contrarian view of the five-factor approach to personality description. Psychol. Bull. 117 (2), 187–215.

Cavnar, W.B., Trenkle, J.M., 1994. N-gram-based text categorization. In: Proceedings of Third Annual Symposium on Document Analysis and Information Retrieval (SDAIR-94), pp. 161–175.

Coltheart, M., 1981. The mrc psycholinguistic database. Q. J. Exp. Psychol. 33 (4), 497–505.
Corder, G.W., Foreman, D.I., 2009. Nonparametric Statistics for Non-Statisticians: A Step-by-Step Approach. Wiley, New Jersey.
Costa Jr, P.T., McCrae, R.R., 1992. Revised NEO Personality Inventory (NEO PI-R) and NEP Five-Factor Inventory (NEO-FFI): Professional Manual, Psychological Assessment Resources.
Costa Jr., P.T., McCrae, R.R., 1994. Set like plaster? Evidence for the stability of adult personality. In: Can Personality Change? American Psychological Association, pp. 21–40.
Costa Jr, P.T., McCrae, R.R., 1997. Longitudinal stability of adult personality. In: Hogan, R., Johnson, J.A., et al. (Eds.), Handbook of Personality Psychology. Academic Press, Inc, San Diego, USA, pp. 269–290.
Cuperman, R., Ickes, W., 2009. Big Five predictors of behavior and perceptions in initial dyadic interactions: personality similarity helps extraverts and introverts, but hurts "disagreeables". J. Pers. Soc. Psychol. 97 (4), 667.
De Choudhury, M., Lin, Y.-R., Sundaram, H., Candan, K.S., Xie, L., Kelliher, A., 2010. How does the data sampling strategy impact the discovery of information diffusion in social media? In: Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media (ICWSM'10), Washington, DC, USA.
Funder, D.C., 2012. Personality Puzzle. W.W. Norton, Incorporated.
Gerani, S., Zhai, C., Crestani, F., 2012. Score transformation in linear combination for multi-criteria relevance ranking. In: Advances in Information Retrieval, Lecture Notes in Computer Science, vol. 7224, pp. 256–267.
Gimpel, K., Schneider, N., O'Connor, B., Das, D., Mills, D., Eisenstein, J., Heilman, M., Yogatama, D., Flanigan, J., Smith, N.A., 2011. Part-of-speech tagging for Twitter: annotation, features, and experiments. In: Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies (HLT '11), Portland, OR, USA, pp. 42–47.
Goel, A., Gupta, P., Sirois, J., Wang, D., Sharma, A., Gurumurthy, S., 2015. The who-to-follow system at twitter: strategy, algorithms, and revenue impact. Interfaces 45 (1), 98–107.
Golbeck, J., Robles, C., Edmondson, M., Turner, K., 2011. Predicting personality from Twitter. In: IEEE Third International Conference on Social Computing (Social-Com/PASSAT), Boston, MA, USA, pp. 149–156.
Gottschalk, L.A., Gleser, G.C., 1969. The Measurement of Psychological States through the Content Analysis of Verbal Behavior. University of California Press.
Hellriegel, D., Slocum, J.W., Woodman, R.W., 1987. Organizational Behavior. West Publ. Co..
Hu, R., Pu, P., 2010. A study on user perception of personality-based recommender systems. In: User Modeling, Adaptation, and Personalization, Lecture Notes in Computer Science, vol. 6075, pp. 291–302.
Hu, R., Pu, P., 2011. Enhancing collaborative filtering systems with personality information. In: Proceedings of the Fifth ACM Conference on Recommender Systems (RecSys '11), Chicago, IL, USA, pp. 197–204.
Lewis, D.D., Yang, Y., Rose, T.G., Li, F., 2004. RCV1: a new benchmark collection for text categorization research. J. Mach. Learn. Res. 5, 361–397.
Liben-Nowell, D., Kleinberg, J., 2003. The link prediction problem for social networks. In: Proceedings of the 12th International Conference on Information and Knowledge Management (CIKM '03), New Orleans, LA, USA, pp. 556–559.
Lü, L., Zhou, T., 2011. Link prediction in complex networks: a survey. Physica A: Stat. Mech. Appl. 390 (6), 1150–1170.
Mairesse, F., Walker, M., Mehl, M., Moore, R., 2007. Using linguistic cues for the automatic recognition of personality in conversation and text. J. Artif. Intell. Res. 30, 457–500.
McCrae, R.R., Costa Jr, P.T., 1989. More reasons to adopt the five-factor model. Am. Psychol. 44 (2), 451–452.
McCrae, R.R., Costa, P.T., 1982. Self-concept and the stability of personality: cross-sectional comparisons of self-reports and ratings. J. Pers. Soc. Psychol. 43 (6), 1282–1292.
McPherson, M., Smith-Lovin, L., Cook, J.M., 2001. Birds of a feather: homophily in social networks. Annu. Rev. Sociol. 27 (1), 415–444.
Moss, H.A., Susman, E.J., 1980. Longitudinal study of personality development. In: Constancy and Change in Human Development. Harvard University Press, pp. 530–595.
Noller, P., Law, H., Comrey, A.L., 1987. Cattell, Comrey, and Eysenck personality factors compared: more evidence for the five robust factors?. J. Pers. Soc. Psychol. 53 (4), 775–782.
Pennebaker, J.W., Chung, C.K., Ireland, M., Gonzales, A., Booth, R.J., 2007. The development and psychometric properties of LIWC2007. This article is published by LIWC Inc, Austin, Texas 78703, USA in conjunction with the LIWC2007 software program. ⟨http://www.liwc.net/LIWC2007LanguageManual.pdf⟩.
Pennebaker, J.W., Mehl, M.R., Niederhoffer, K.G., 2003. Psychological aspects of natural language use: our words, our selves. Annu. Rev. Psychol. 54 (1), 547–577.
Porter, M., 1997. An algorithm for suffix stripping. In: Readings in Information Retrieval. Morgan Kaufmann Publishers Inc., pp. 313–316.
Romero, D.M., Kleinberg, J.M., 2010. The directed closure process in hybrid social-information networks, with an analysis of link formation on Twitter. In: Proceedings of the Fourth International Conference on Weblogs and Social Media (ICWSM 2010), Washington, DC, USA.
Rosenberg, S.D., Tucker, G.J., 1979. Verbal behavior and schizophrenia: the semantic dimension. Arch. Gen. Psychiatry 36 (12), 1331–1337.
Rowe, M., Stankovic, M., Alani, H., 2012. Who will follow whom? Exploiting semantics for link prediction in attention-information networks. In: The Semantic Web—ISWC 2012, Lecture Notes in Computer Science, vol. 7649. Springer-Verlag, pp. 476–491.
Salton, G., McGill, M.J., 1983. Introduction to Modern Information Retrieval. McGraw-Hill, New York.
Salton, G., Wong, A., Yang, C., 1975. A vector space model for automatic indexing. Commun. ACM 18 (11), 613–620.
Selfhout, M., Burk, W., Branje, S., Denissen, J., van Aken, M., Meeus, W., 2010. Emerging late adolescent friendship networks and Big Five personality traits: a social network approach. J. Pers. 78 (2), 509–538.
Selfhout, M., Denissen, J., Branje, S., Meeus, W., 2009. In the eye of the beholder: perceived, actual, and peer-rated similarity in personality, communication, and friendship intensity during the acquaintanceship process. J. Pers. Soc. Psychol. 96 (6), 1152–1165.
Sherman, R.A., Nave, C.S., Funder, D.C., 2012. Properties of persons and situations related to overall and distinctive personality-behavior congruence. J. Res. Pers. 46 (1), 87–101.
Shevade, S.K., Keerthi, S.S., Bhattacharyya, C., Murthy, K.R.K., 2000. Improvements to the smo algorithm for svm regression. IEEE Trans. Neural Netw. Learn. Syst. 11 (5), 1188–1193.
Tkalcic, M., Kunaver, M., Tasic, J., Košir, A., 2009. Personality based user similarity measure for a collaborative recommender system. In: Proceedings of the Fifth Workshop on Emotion in Human–Computer Interaction-Real World Challenges, pp. 30–37.
Tommasel, A., Corbellini, A., Godoy, D., Schiaffino, S., 2015. Exploring the role of personality traits in followee recommendation. Online Inf. Rev. 39 (6) ⟨http://www.emeraldinsight.com/doi/abs/10.1108/OIR-04-2015-0107⟩.
Tupes, E.C., Christal, R.E., 1961. Recurrent Personality Factors Based on Trait Ratings, Technical Report. Lackland Air Force Base, US Air Force, TX.
Tupes, E.C., Christal, R.E., 1992. Recurrent personality factors based on trait ratings. J. Pers. 60 (2), 225–251.
Waller, N.G., Ben-Porath, Y.S., 1987. Is it time for clinical psychology to embrace the five-factor model of personality? Am. Psychol. 42 (9), 887–889.
Wu, S., 2012. Linear combination of component results in information retrieval. Data Knowl. Eng. 71 (1), 114–126.
Wu, W., Chen, L., He, L., 2013. Using personality to adjust diversity in recommender systems. In: The 24th ACM Conference on Hypertext and Social Media (HT' 13), Paris, France, pp. 225–229.