Fusing Social Media Cues: Personality Prediction from Twitter and Instagram

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ABSTRACT

Incorporating users' personality traits has shown to be instrumental in many personalized retrieval and recommender systems. Analysis of users' digital traces has become an important resource for inferring personality traits. To date, the analysis of users' explicit and latent characteristics is typically restricted to a single social networking site (SNS). In this work, we propose a novel method that integrates text, image, and users' meta features from two different SNSs: Twitter and Instagram. Our preliminary results indicate that the joint analysis of users' simultaneous activities in two popular SNSs seems to lead to a consistent decrease of the prediction errors for each personality trait.

Keywords

social media mining, user modelling, personality computing

1. INTRODUCTION AND RELATED WORK

In recent years, social networking sites (SNSs) have become a popular means for information exchange and social interactions. Users' presence and their online activities spread across different platforms, each with their own interactive and content-oriented characteristics. The user-generated content has been shown to yield important insights into users' interests, preferences, and sentiments toward various topics. However, to date, the analysis of users' explicit and latent characteristics has been typically restricted to a single SNS.

Personality is a psychological construct accounting for individual differences in people [9]. The most widely used *Five-Factor Model* comprises five traits: *Openness, Conscientiousness, Extraversion, Agreeableness* and *Neuroticism* [6]. As users leave rich traces of their digital activities through SNSs, the collected data has become an important resource for inferring users' personality traits. The research domain has been gathered under the umbrella of *personality computing* [9]. One of the earliest works was published by Golbeck et al. [2], in which a variety of features related to a user's social network membership and language use in microblogs were investigated. Quercia et al. [7] applied features related to the user's activity and reputation in Twitter. Kosinski et al. [4] have collected a large dataset of Facebook users and demonstrated the predictive value of users' *Likes* to infer personality traits. The frequently applied approaches focused on data from a single SNS. Nowadays, as users often provide clues that enable the linkage between their respective profiles in different SNSs, there is an increase of amount of multi-network data. In this work, we present a range of multimodal personality regressors incorporating user information from two SNSs and evaluate them against regressors trained on data acquired from a single SNS.

2. METHOD

Foundational concepts of social network research, including Lewin's field theory, motivate joint analysis of different networks of an individual, including the relations between personality traits and their manifestations in different SNSs. Previous studies have demonstrated that the visual [1], linguistic [2] and meta [7] features extracted from users' generated online content can be instrumental for inferring personality traits. As the present work analyses users' activities in two popular SNSs, Instagram and Twitter, primarily used to share images and text, we developed a pipeline that extracts image, linguistic, and users' meta features related to their reputation and influence. For Instagram images, the annotations include: Pleasure-Arousal-Dominance (PAD), brightness, saturation, hue-related and content-based features such as person's face or full body, drawing inspiration from features used in the emotion detection technique proposed in [5]. For extraction of linguistic features from tweets and Instagram image captions, we adapted our annotation system [8], that integrates natural language processing resources (e.g., LIWC, ANEW) and classifiers (e.g., Dialog Acts, Sentiment). We also included users' reputation and influence meta features based on users' publicly available counts: number of followers and followees, 'Klout' and adaptation of 'TIME' influence scores [7].

To obtain compact feature representations of the accessible information, we compute for each extracted feature: mean, standard deviation, minimum, maximum and median. We address the curse of dimensionality and noise reduction through subsampling with the F-statistic. We use random forest regression to build a low variance and low bias model of personality trait characteristics by averaging over regression tree decisions. The variable importance ranking

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	O	C	E	A	N	AVG
B	0.75	0.75	1.04	0.67	0.98	1.14
T_m	0.74	0.78	1.16	0.71	1.07	0.89
I_i	0.80	0.70	0.98	0.74	0.90	0.83
T_{lm}	0.75	0.73	0.92	0.71	0.80	0.78
$T_m I_i$	0.62	0.66	0.92	0.69	0.92	0.77
I_l	0.62	0.66	0.92	0.69	0.92	0.76
T_l	0.73	0.66	0.96	0.63	0.75	0.75
$T_m I_l$	0.65	0.68	0.86	0.60	0.79	0.72
$T_l I_l$	0.61	0.68	0.86	0.63	0.76	0.71
$T_m I_{li}$	**0.51**	0.68	0.86	**0.55**	0.88	0.70
$T_l I_{li}$	0.64	**0.65**	0.87	**0.55**	**0.73**	0.69
$T_{lm} I_{li}$	0.53	0.67	**0.71**	0.56	0.83	**0.66**

Table 1: RMSE with features from (T)witter and (I)nstagram; and (B)aseline score: average value for a dimension. Subscripts indicate sets of features used: (l)inguistic, i(mage), (m)eta.

induced by random forests further reduces the number of features considered for each personality trait.

Data collection

We recruited native English SNS users of high reputation located in the United States of both, Instagram and Twitter, via Amazon Mechanical Turk. An administered questionnaire asking for their informed consent included the 44-item Big Five Inventory personality questionnaire [3] and quality assurance cross-checks and comprehension questions. The aggregated answers were used to infer participants' five basic personality traits (openness to experience, conscientiousness, extraversion, agreeableness, neuroticism); each trait scored from 1 to 5. We then crawled data from participants' SNSs accounts, filtering out those with fewer than 30 Instagram images or 30 tweets: our final set comprises of 62 users with sufficient amount of data in both SNSs.

3. RESULTS AND CONCLUSIONS

Table 1 presents personality regressor performances over different sets of features, using root-mean square error (RMSE) calculated over 5 independent, 10-fold cross-validation runs, one for each personality trait. Results indicate that both, the set of features selected and the choice of the SNS or their combination, yield differences in regressor performance. The best results, overall and for each personality trait, are obtained integrating features extracted from both SNSs. The overall best performing regressor, $T_{lm}I_{li}$, uses a complete set of features (linguistic, image, and meta). It is also most informative for Extraversion (RMSE: 0.71). Conscientiousness (RMSE: 0.65), Agreeableness (RMSE: 0.55) and Neuroticism (RMSE: 0.73) are best regressed with the combination of linguistic features of tweets and captions with image features, while Openness (RMSE: 0.51) using Twitter's linguistic and meta plus Instagram image features. As there is no common, publicly available personality data-set that includes data from multiple SNSs, in Table 2 we present the results of the $T_{lm}I_{li}$ regressor along the state-of-the-art personality regression systems over different data-sets. In the table we adopt the metrics used in the original papers [7, 4, 2]. Note that each study used different data sets acquired from different SNSs, and while the presented results provide insights on the performance of each regressor, different regressors are not directly comparable.

	RMSE		MAE		PCC	
	T [7]	$\mathbf{T_{lm}I_{li}}$	**T** [2]	$\mathbf{T_{lm}I_{li}}$	**FB** [4]	$\mathbf{T_{lm}I_{li}}$
O	0.69	**0.51**	0.12	**0.11**	0.43	**0.74**
C	0.76	**0.67**	0.14	**0.11**	0.29	**0.76**
E	0.88	**0.71**	**0.16**	0.17	0.40	**0.65**
A	0.79	**0.50**	0.12	0.12	0.30	**0.34**
N	0.85	**0.73**	0.19	**0.16**	0.30	**0.71**
AVG	0.79	**0.73**	0.15	**0.13**	0.30	**0.64**

Table 2: Personality traits regression accuracy of $T_{lm}I_{li}$ along the state-of-the-art systems inferred from different SNSs: (T)witter, (I)nstagram, FB - Facebook, in terms of RMSE, MAE - Mean Absolute Error, PCC - Pearson Correlation Coefficient.

Our novel approach to Internet user personality recognition integrates user data from two SNSs. The presented method can easily be adapted to other SNSs and for inferring other types of explicit and latent user characteristics. Our first results indicate the potential of the proposed joint, multi-modal analysis of user-generated data from different SNSs, justifying the ongoing detailed investigation, which also addresses theoretical issues such as soundness conditions of such integration and includes a large scale evaluation of the inferred users' personality traits scores applied in recommendation systems.

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