Modeling the Personality of Participants During Group Interactions

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Abstract. In this paper we target the automatic prediction of two personality traits, Extraversion and Locus of Control, in a meeting scenario using visual and acoustic features. We designed our task as a regression one where the goal is to predict the personality traits' scores obtained by the meeting participants. Support Vector Regression is applied to thin slices of behavior, in the form of 1-minute sequences.

Keywords: Personality Modeling, Support Vector Regression, Adaptivity, Group Interactions.

1 Introduction

Personality is the complex of all the attributes - behavioral, temperamental, emotional and mental - that characterize a unique individual. Humans have the tendency to understand and explain other humans' behavior in terms of stable properties that are variously assorted on the basis of the observation of everyday behavior. In this sense, the attribution of a personality and its usage to infer about the others is a fundamental property of our naïve psychology and therefore it is an important aspect in social interaction.

In everyday intuition, the personality of a person is assessed along several dimensions: we are used to talk about an individual as being (non-)open-minded, (dis-) organized, too much/little focused on herself, etc. Several existing theories have formalized this intuition in the form of multi-factorial models, whereby an individual's personality is described in terms of a number of more fundamental dimensions known as traits, derived through factorial studies. A well known example of a multi-factorial model is the Big Five [1] which owes its name to the five traits it takes as constitutive of people's personality:

1. Extraversion vs. Introversion (sociable, assertive, playful vs. aloof, reserved, shy);
2. Emotional stability vs. Neuroticism (calm, unemotional vs. insecure, anxious);
3. Agreeableness vs. Disagreeable (friendly, cooperative vs. antagonistic, faultfinding);

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4. Conscientiousness vs. Un-conscientiousness (self-disciplined, organized vs. inefficient, careless);
5. Openness to experience (intellectual, insightful vs. shallow, unimaginative)

Despite some known limits ([2]; [3]), over the last 50 years the Big Five has become a standard in Psychology. Experiments show that personality traits influence many aspects of task-related individual behavior (e.g. leadership ability [4], attitude toward machines [5]) and also the attitude toward some basic dimensions of adaptivity [6].

Although in some applications it would be possible to acquire personality information by asking the users directly ([7];[8]), in other cases it would be very helpful to do it automatically. For instance, social network websites could analyze text messages to try to mach personalities and increase the chances of a successful relationship [9]. Tutoring systems could be more effective if they could adapt themselves to the learner's personality [10]. Some studies proved that users' evaluation of conversational agents depends on their own personality ([11];[12]). Consequently, a requirement for such systems to adapt to the users' personality, like humans do, is emerging ([13]; [14]). Because of its relevance in social settings, information on user' personality could be useful in personalized support to group dynamics [15].

The work presented in this paper intends to contribute to the specific task of the automatic analysis of people's personality during social interaction through the analysis of acoustic and visual features. We focus on two personality traits: Extraversion and Locus of Control.

Extraversion, one of the Big Five traits, is the quantity and intensity of a subject's interpersonal reactions, emotional expressiveness, and sociability. Correlation has been shown between extraversion and verbal behavior, in particular with prosodic features: higher pitch and higher variation of the fundamental frequency [16], fewer and shorter silent and filled pauses, and higher voice quality and intensity [17]. Moreover, studies on the differences between the communication styles of introverts and extroverts suggest that the latter speak more and more rapidly, with fewer pauses and hesitations [18].

Locus of Control (LoC) reflects a stable set of belief about whether the outcomes of one's actions are dependent upon what the subject does (internal orientation) or on events outside of her control (external orientation) [19]. That is, LoC measures whether causal attribution [20] for one's behavior or beliefs is made to oneself or to external events or circumstances. It has been used as an empirical tool in several domains; for instance, it was shown that people, who feel they are the source or cause of their own attitudes and behaviors (internal LoC), tend to see the computer as a tool that they can control and use to extend their capabilities [21]. On the other hand, those who attribute their own behavior or attitudes to external factors (external LoC) are much prone to regard computers as an autonomous, social entity with which they are need to interact.

In this work, we employ regression analysis on a set of acoustic and visual features extracted from a 1-minute slice of the interaction to predict the values of Extraversion and LoC that a given participant would score on a validated questionnaire.

In relevant respects, the task is similar to the one we, as humans, are routinely involved in when judging about strangers' personality from very short behavioral sequences. Those "intuitions", based on so-called thin slices of behavior, and the process they come by have been the subject of extensive investigation by social psychologists in the last years [23].

2 Previous and Related Works

In [24] the relative frequency of function words and of word categories based on Systemic Functional Grammar are used to train Support Vector Machines (SVMs) with linear kernel for the recognition of Extraversion and Emotional Stability. The data concerning the two personality traits were based on self-reports.

In [25] and [26] the recognition of personality in dialogue is examined. Later, classification, regression and ranking models were applied to the recognition of the Big Five personality traits and self-reports data were compared with observed one [27]. The usefulness of different sets of (acoustic and textual) features, suggested by the psycholinguistic and psychosocial literature, were systematically examined. Mairesse et al.'s work shows that Extraversion is the easiest personality trait to model from spoken language and that prosodic features play a major role. At the same time, their results turn out to be closer to those based on observed personality than on self-reports.

In [28] Naive Bayes and SVMs with linear kernel were trained on a corpus of personal weblogs, using n-gram features extracted from the dataset, for four of the Big Five traits. A major finding of Oberlander and Nowson's work is that the model for Agreeableness was the only one to outperform the baseline. Their personality data were obtained through self-reports.

We are not aware of any attempt to predict personality traits in a social setting besides our previous work [29] in which we used SVM to classify the level of Extraversion and LoC of the participants in 3 classes: low, medium and high.

3 The Mission Survival Corpus

For this study, we used a multimodal corpus of multi-party meetings in which groups of four people were involved in a social interaction (see [30] for a more comprehensive description), the so-called Mission Survival Task (MST), often used in experimental and social psychology to elicit decision making processes in small groups [31]. The MST task consists reaching a consensus on ranking a list of 12 specific items useful to allow survival after a plane crashing. First each participant expresses his/her own personal opinion and then the group discusses each individual proposal, weights the decision and finally ranks the 12 items according to their importance for survival.

Audio was recorded through close-talk microphones worn by each participant and through one omni-directional microphone placed in the middle of the table. Eight cameras recorded the visual context, four from the corners of the room and the other four from the closer walls surrounding the table.

The corpus consists of audio and video recordings of 12 meetings for a total of over 6 hours. Annotations of speech activities and 3D tracking of body activities were automatically extracted, as described below.

The personality traits of all participants were collected by means of standard questionnaires validated on the Italian language, namely the Italian version of Craig's Locus of Control of Behavior scale [32], and the part of Big Marker Five Scales related to the Extraversion dimension [33].

The former is composed by 17 items, with a rating scale from 0 to 5 points, while the Extraversion questionnaire is composed by 10 items, with a rating scale from 1 to 7. The individual LoC and Extraversion scores, characterizing personality traits of each participant, were obtained by summing the points of each item. The mean of the LoC scores for our sample is 27 (standard deviation 7.67; variance 58.86), while for the Extraversion the mean is 46 (standard deviation 8.02; 64.30). Both are consistent with Italian distribution reported by the validation studies above.

4 Feature Extraction

The goal of the learning task is to predict the scores on the two traits of each individual participants in the context of the social interaction. We therefore extracted a number of acoustic and visual features for all the participants and we modeled the learning task as a regression on the combinations of the vector representing the acoustic and visual features of the individual target, combined with the vectors representing the features of the other participants.

4.1 Acoustic Features

Using the speech feature extraction toolbox, developed by the Human Dynamics group at Media Lab[1], we extracted 22 acoustic features from the audio recordings.

The speech features were computed on a 1-minute audio windows. As suggested by previous works ([34], [35] and [36]), 1-minute size is large enough to compute the features in a reliable way, while being small enough to capture the transient nature of social behavior. Table 1 lists the set of acoustic features extracted from the audio corpus. Their relevance for the analysis of human behavior in social setting was discussed by [37]. They grouped them in four classes measuring vocal signals in social interactions: 'Activity', 'Emphasis', 'Influence', and 'Mimicry'. These four classes of features are honest signals, sufficiently expensive to fake that they can form the basis for a reliable channel of communication, and they can be used to predict and explain the human behavior in social interactions.

Emphasis is often considered a signal of how strong is the speaker's motivation. Moreover, the consistency of emphasis (the lower the variations, the higher the consistency) could be a signal of mental focus, while variability may signal an openness to influence from other people. Emphasis is measured by the variation in prosody, i.e. pitch and amplitude. For each voiced segment, the mean energy, frequency of the fundamental format and the spectral entropy are extracted (F1, F2, F3, F4, F5, F6 and F8). The mean-scaled standard deviation of these extracted values is then estimated by averaging over longer time periods (F9, F10, F11, F12, F13, F14 and F16).

[1] http://groupmedia.media.mit.edu/data.php

Table 1. Extracted acoustic features (Mean and Standard Deviation calculated on 1 minute)

LABELS	ACOUSTIC FEATURES	Sel_F		Sel_B	
		Extra	LOC	Extra	LOC
F1 - E	Mean Formant Frequency (Hz)	*		* ▲	* ▲
F2 - E	Mean Confidence in formant frequency	*		* ▲	* ▲
F3 - E	Mean Spectral Entropy			▲	* ▲
F4 - E	Mean of Largest Autocorrelation Peak	* ▲		* ▲	*
F5 - E	Mean of Location of Largest Autocorrelation Peak	*		* ▲	* ▲
F6 - E	Mean Number of Autocorrelation Peaks	▲		▲	▲
F7 -A	Mean Energy in Frame	*	* ▲	* ▲	* ▲
F8 - E	Mean of Time Derivative of Energy in Frame	*	*	* ▲	* ▲
F9 - E	SD of Formant Frequency (Hz)	* ▲		* ▲	
F10 - E	SD of Confidence in formant frequency			* ▲	
F11 - E	SD of Spectral Entropy	* ▲	▲	* ▲	* ▲
F12 - E	SD of Value of Largest Autocorrelation Peak	* ▲	▲	* ▲	▲
F13 - E	SD of Location of Largest Autocorrelation Peak	*		* ▲	* ▲
F14 - E	SD of Number of Autocorrelation Peaks		*	▲	* ▲
F15 - A	SD of Energy in Frame	* ▲		* ▲	* ▲
F16 - E	SD of Time Derivative of Energy in Frame	*		* ▲	▲
F17 - A	Average length of voiced segment (seconds)			▲	* ▲
F18 - A	Average length of speaking segment (seconds)	*		* ▲	▲
F19 - A	Fraction of time speaking	* ▲		* ▲	*
F20 - A	Voicing rate	*		* ▲	▲
F21 - I	Fraction speaking over	*		* ▲	*
F22 - M	Average number of short speaking segments	*		* ▲	* ▲

*= features for the target subject, and ▲= features for the other subjects selected by the two correlation-based selection procedures.

Activity, meant as conversational activity level, usually indicates interest and excitement. Such level is measured by the z-scored percentage of speaking time (F7, F17, F18, F19 and F20). For this purpose, the speech stream of each participant is first segmented into voiced and non-voiced segments, and then the voiced ones are split into speaking and non-speaking.

Influence, the amount of influence each person has on another in a social interaction, was measured by calculating the overlapping speech segments (F21). Influence is a signal of dominance. Moreover, its strength in a conversation can serve as an indicator of attention. It is difficult, in fact, for a person maintain the rhythm of the conversational turn-taking without paying attention to it.

Mimicry, meant as the un-reflected copying of one person by another during a conversation (i.e. gestures and prosody of one are "mirrored" by the other), is expressed by short interjections (e.g. "yup", "uh-huh",) or back-and-forth exchanges consisting of short words (e.g. "OK?", "done!"). Usually, more empathetic people are more likely to mimic their conversational partners: for this reason, mimicry is often used as an unconscious signal of empathy. Mimicry is a complex behavior and therefore difficult to computationally measure. A proxy of its measure is given by the z-scored frequency of these short utterances (< 1 second) exchanges (features F22).

4.2 Visual Features

Regarding the visual context, we mainly focused on few features related to the energy (fidgeting) associated with head, hands and body (see Table 2).

Table 2. Extracted visual features, related to Head, Hands, and Body

LABELS	ACOUSTIC FEATURES	Sel_F		Sel_B	
		Extra	LOC	Extra	LOC
F23	Head fidget-ing		*	▲	* ▲
F24	Hands fidg-eting			▲	▲
F25	Body fidget-ing	*		*	*

The fidgeting features have been automatically annotated by employing the MHI (Motion History Images) techniques [38], which use skin region features and temporal motions to detect repetitive motions in the images and associate such motions to an energy value in such a way that the higher the value, the more pronounced the motion.

5 Modelling Personality Traits Using Support Vector Regression

It is a tenet of this study that personality shows up in social behavior, and that our acoustic and visual features are appropriate to form the 'thin slices' an automatic system can exploit to predict personality traits. Our goal is therefore to model and predict personality traits by considering the behavior of a subject in a 1-minute temporal window; a task similar to that of a psychologist asked to assess personality traits based on thin slices of behavior.

A regression approach was exploited, based on Support Vector Regression (SVR) [39]. Similarly to Support Vector Classification, it produces models that only depend on a subset of the training data, thanks to the cost function that ignores any training data closer to the model prediction than a threshold ε. Moreover, SVR ensures the existence of a global minimum and the optimization of a reliable generalization bound. In ε-SVR the goal is to find a function $f(x)$ that has at most ε deviation from the target for all the training data and at the same time is as flat as possible [40].

We used an ε-SVR with a Radial Basis Function (RBF) kernel. The cost parameter C, the kernel parameter γ and the threshold ε were estimated through the grid technique by cross-fold validation using a factor of 10.[2]

5.1 Experimental Design

Personality can be assessed in two different manners, depending on the role social context is assigned. One might argue that the sole consideration of the target subject' behavior (her thin slices) is enough: the way she/he moves, the tone and energy of her/his voice, etc., are sufficiently informative to get at her personality. A different view maintains that personality manifestation/assessment is sensitive to the social context: the same behavior might have a different import if produced in a given social environment than in another. We formulate the following hypothesis:

Hypothesis 1. The consideration of the social context improves personality assessment.

For our purposes, the social context is encoded through thin slices of the other members of the group.

A second hypothesis we investigate is that personality assessment can be made more economical by limiting the analysis to subsets of the features discussed above. In this paper the following two feature selection procedures are investigated.

Correlation-based feature selection. The correlation-based feature selection technique [41] selects a subset of features that highly correlate with the target value and have low inter-correlation. This method is used in conjunction with a search strategy, typically Best First that searches the features subset space through a greedy hill-climbing strategy with backtracking. The search may start with an empty set of features and proceed forward (forward search) or with the full set of features and go backward (backward search), or proceed in both directions.

We used the backward and the forward search, applying them both to the features of the target subject and to those of the other members of the group. Table 3 and Table 4 report the results of the two selection procedures for the two personality traits. It can be noticed that the forward search (Sel_F) produces a much larger subset of features for Extraversion than for LoC. The backward search (Sel_B), in turn, yields more numerically balanced subsets/

ANOVA-based Feature Selection. ANOVA-based feature selection was performed only on the acoustic features of the target subject, by comparing their means through ANOVA: each feature was treated as a dependent variable in two between-subject analysis of variance, with factor Extraversion (3 levels: L, score<-1σ, M, -1σ≤score≤1σ; H, score>1σ) and LoC (3 levels: L, M, H); significance level was p<.05. No adjustment for multiple comparisons was performed, in order to have a more liberal test. Only the features for which the analysis of variance reported significant results were retained, for the each factor, namely: F1, F2, F6, F14, a subset of the

[2] We used the LibSVM tool, available at http://www.csie.ntu.edu.tw/~cjlin/libsvm/

Emphasis class, and F21, the Influence feature, for Extraversion, and F1, F6, F14, the same subset of the Emphasis class apart for the mean energy, and F22, the Mimicry feature, for LoC.

We formulate the following hypothesis.

Hypothesis 2. The selected subsets improve the performance

A within-subject design was exploited to address the two hypotheses, with factors 'Target' and 'Others', each relating to different arrangements of the target subject's (Target) and of the other participants' (Others) features.

- 'Target' has 3 levels: (i) All features (AllFeat); (ii) the features obtained by means of the correlation-based approach (either Sel_F or Sel_B, see below); (iii) the features provided by the Anova-based procedure (Sel_A).
- 'Others' has 4 levels: the same three as for Target, plus a level corresponding to the absence of any features for the other participant (No_Feat). The presence of this level allows to address the contextual hypothesis discussed above.

For each experimental condition, the training instances included the average values of the relevant acoustic and visual feature, computed over a 1-minute window. The analysis was conducted through a leave-one-out procedure. At each of the 48 folds, training was conducted on the data of all but one subject, who was used for testing.

6 Results

Our figure of merit is the squared regression error, SSEER=$(y_{obs}-y_{pred})^2$. Results are compared to those obtained by the base model that always returns the average (27 for LoC and 47 for Extraversion. Its mean SSERR are 59.70 (SD=60.14) for LoC and 63.63 (SD=93.35) for Extraversion.

T-tests ($p<.05$ with Bonferroni corrections) were first conducted comparing the performance of the features obtained by means of the forward (Sel_F) and backward (Sel_B) search for the correlation-based method in the following conditions: (SEL_F, No_Feat) vs. (Sel_B, No_Feat); (SEL_F, All_Feat) vs. (Sel_B, All_Feat); (Sel_F, Sel_F) vs. (Sel_B, Sel_B); (All_Feat, Sel_F) vs. (All_Feat, Sel_B). The two sets of features never produced significant differences for Extraversion, while Sel_B was consistently superior to Sel_F for LoC. Hence, in the following we will consider only Sel_F for Extraversion and Sel_B for LoC.

A repeated measure analysis of variance for Extraversion revealed only a Target main effect ($F_{1.435,\ 47}=6.802$, $p=.004$, with Greenhouse-Geisser correction). According to pairwise comparisons on Target's marginals, Target=All_Feat is significantly lower than the other two levels ($p<.0001$). Finally, all the conditions with Target=All_Feat have SSERR values that are not pairwise statistically different (t-tests, $p<0.05$, Bonferroni correction). Hence, no condition is better than (All_Feat, No_Feat) and there is no evidence that the exploitation of the context (as encoded by the Others' features) improves the results. In other words, both Hypothesis 1 and Hypothesis 2 cannot be maintained. Finally, (All_Feat, No_Feat) is better than the baseline.

Table 3. Average SSERR and standard deviations for Extraversion

		Others				
		No_Feat	All_Feat	Sel-B	Sel_A	
Target	All_Feat	19.45 (58.38) *	25.04 (69.98) *	24.13 (61.41) *	26.20 (72.45) *	23.78 (65.69)
	Sel-B	34.09 (68.65)	44.64 (80.93) *	26.63 (69.45) *	45.92 (80.23)	37.05 (75.21)
	Sel_A	35.02 (76.09) *	39.63 (115.06)	49.48 (84.57)	40.57 (102.43) *	41.27 (95.89)
		29.53 (67.99)	36.44 (90.46)	33.41 (72.84)	37.56 (85.79)	

* = conditions that are significantly better than the baseline.

Table 4. Average SSERR and standard deviations for LoC

		Others				
		No_Feat	All_Feat	Sel_F	Sel_A	
Target	All_Feat	17.78 (45.11) *	11.87 (30.23)	12.58 (32.17)	15.85 (30.03)	14.52 (36.38)
	Sel_F	33.82 (56.42)	27.35 (60.58) *	13.07 (34.91)	39.65 (54.27)	28.47 (53.00)
	Sel_A	33.23 (50.94)	29.73 (94.92)	53.32 (59.90)	26.39 (61.33)	35.69 (69.09)
		28.31 (51.22)	22.98 (67.31)	26.32 (47.82)	27.30 (52.44)	

* = conditions that are significantly better than the baseline.

Another repeated measure ANOVA for LoC produced both Target ($F_{1.546, 47}$=12.362, p<.0001) and Target*Others ($F_{1.815, 47}$=4.838, p<0.05) effects. Concerning marginals, Target=All_Feat is better than the others (pairwise t-tests, p<0.05, Bonferroni correction). The interaction is due to Others=Sel_B that produces very low SSERR values in two cases out of three (see Table 3). Conditions (All_Feat, All-Feat), (All_Feat, Sel_B) and (Sel_B, Sel_B) do not pairwise statistically differ, provide the best results and are all better than the baseline. Hence, for LoC both Hypothesis 1 and Hypothesis 2 are verified, the latter limited to a few cases.

7 Discussion and Conclusions

This paper aims to contribute to advance the state of the art in user modeling by demonstrating the feasibility of exploiting personality traits. We based our approach on the assumption that a) personality shows up in the course of social interaction and b) that thin slices of social behavior are enough to allow personality traits classification. The first assumption was realized by exploiting classes of acoustic features encoding specific aspects of social interaction (Activity, Emphasis, Mimicry, and Influence) and three visual features (head, body, and hands fidgeting). As to the second, we considered 1-minute long behavioral sequences. The resulting task for the regression model is similar to that of an expert (e.g., a psychologist) that must provide a personality assessment of strangers based only on short sequences of their behavior.

Based on those assumptions, we designed and executed a regression study addressing two hypotheses: a) that two simple feature selection procedures could provide a smaller, but still effective, subset of features, and b) that the encoding of the social contexts (in the form of the other group members' features) could contribute to regression performance. The data analysis shows that the two traits we have considered behave differently concerning those hypotheses. In the case of Extraversion, no feature selection procedure provided results that were no worse than those obtained by means of All_Feat for the target subject, and there was no evidence that the consideration of the interaction context improve performance. LoC, in turn, seems more capable of taking advantage of one of the feature selection procedure (Sel_B) and, what is more, there are clear signs that LOC's manifestation (and/or understanding by an external observer) improves if the social context is considered.

We believe that, if confirmed by further studies, these differences are of some theoretical and practical importance: theoretically, the different contextual sensitivity of Extraversion and LoC is probably a reflection of deep differences between these two traits: Extraversion is more directly linked to (certain) behavioral manifestations than LoC, for which the social context acts a moderating factor. Practically, our study not only shows the feasibility of automatically assessing personality traits based on thin slices of behavior; it also indicates which features (sub)sets are more appropriate: all our honest features (limited to the target subject) for Extraversion; the Sel_B subset for both the target and the context, in the case of LoC.

Given these initial encouraging results, several research directions disclose, in particular in the direction of providing more comprehensive personality assessments that can be actually used in realistic setting—e.g., by considering the full set of Big Five scales, or traits that, much as LoC, have been shown to affect the relationship between humans and machines (e.g., Computer Anxiety). Conceivably, this move might require considering other context types, beyond the social ones. Traits such as, e.g., Conscientiousness, might be better detectable during the execution of specific task types, while others, e.g., Computer Anxiety, might better show up when confronted with new tasks and/or pieces of technology. Last, but not least, there comes the important task to connect personality traits to behaviors, attitudes and beliefs of interest in a given scenario for the purposes of personalization and adaptation. One might, therefore, inquiry which interaction style and/or specific product choice are more appropriate to people exhibiting a given level personality profile, and then use this information to adapt the system behavior.

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