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# Socially-Aware Personality Adaptation

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***Abstract*—Emotion and personality are interrelated. A social agent's perceived personality profile influences its affective behavior and vice versa. Having a clear idea and understanding of personality, both from a theoretical perspective and in the context of social agents, is essential for designing intelligent and affective agents. This also includes adaptation to the individual user's needs and preferences, which can be driven by explicit or implicit user feedback to create engaging interactions in the long run. This paper provides a literature overview on how to implement personality for an embodied agent. After presenting personality and personality attraction related theories, we show how personality is conveyed multimodally in current implementations of social agents. Furthermore, adaptation approaches are surveyed, which are used to shape the behavior according to the user preferences.**

***Index Terms*—personality adaptation, socially-aware reinforcement learning, virtual agent, personality expression**

## I. Introduction

"Personality is to emotion as climate is to weather." [1] Revelle and Scherer get to the heart of considering emotion and personality as a pair of linked components. While one's emotions are observable at a certain time in a particular location – and only for a limited period – the character's personality serves as a long-term foundation of personal behavioral patterns, goals and desires, which influence when and how affect will be expressed under which circumstances. It is important to keep this link in mind when developing socially interactive agents, such as virtual agents or social robots. The link between personality and affective behavior can be found in several research experiments. For example, Ochs et al. [2] propose a model of emotions emerging from the personality and current state of social relations, while Gebhard et al. [3] implement affective reactions depending on a social agent's personality profile. Without personality as an input, it might result in unexpected behaviors or emergence of an inhomogeneous personality profile.

Equipping an artificial agent with a compelling personality profile offers the opportunity in particular to reveal trust, establish a relationship to the machine and create an engaging environment. Due to human individual preferences and the diversity of task contexts, the identification of one single, "best" personality profile is a non-trivial task. On the one hand, a user's demographic origin can decide over an utterance being perceived as polite or convincing. On the other hand, the own personality can make the user prefer opposite traits or similar ones. In other scenarios, the task context was identified as a crucial factor, whether a similar or opposite personality is better for reaching the interaction goal most efficiently.

This is where adaptation comes into play, addressing the general question of how to configure a social agent's personality profile given the individual user and task context. However, there is no single straightforward formula to achieve this, which is the reason for why the literature proposes different approaches, ranging from direct mappings of human personality or task context to robot personality, to machine learning approaches.

In this paper, we provide a literature overview of the expression and adaptation of personality for virtual agents and robots. In section II, the Five-Factor-Model, interpersonal circumplex and established theories about interpersonal compatibility are explained to introduce the theoretical foundation to this work. Section III-A outlines how recent research conveys personality regarding different communication channels. Section III-B illustrates which components personality adaptation systems comprise. Finally, it is presented how Socially-Aware Reinforcement Learning and neural networks can be used to adapt the personality of an agent.

## II. Theoretical Background

The psychology offers theories about human personality, interpersonal stance related to personality and similarity attraction, which explain a big proportion of human behavior and preferences for behavior styles. Since humans tend to attribute human characteristics to technical systems [4], computer scientists use findings from the interpersonal interaction and transfer this knowledge to technical systems. This section gives an overview over these theories, some of them are already related to findings from human-agent interactions.

### A. Personality Models

In psychology there are different kinds of personality models. One model type are socio-cognitive approaches, which take the intraindividual cognitive processes and social structures into consideration [5]. For instance, Higgins [6] proposes the regulatory-focus theory, where the perspective of a positive (promotion-focus) or negative outcome (prevention-focus) serve as behavioral guide for a person. This leads to behaviors expressing the personality.

Another model type describes personality in terms of categories, which determine the behavior and therefore how personality will be expressed, among them are: Allport's Trait Theory [7], Cattell's 16 dimensional personality [8], Eysenck's

3 dimensional personality [9], the Myers-Brigg Type Indicator [10] and the HEXACO model [11]. The Five Factor Model, also known as the "Big Five" or "OCEAN" model, is probably one of the most widely used personality frameworks [12], [13]. It describes personality based on the following traits:

- ***O****penness to Experience* covers the tendency to be curious, creative and think in unconventional ways.
- ***C****onscientiousness* covers the tendency to be well-organized, responsible and follow rules.
- ***E****xtraversion* covers the tendency to be sociable, outgoing and assertive.
- ***A****greeableness* covers the tendency to be compliant, friendly and trusting.
- ***N****euroticism* covers the tendency to be impulsive, experience negative emotions and change moods quickly.

Since the OCEAN model is one of the most used ones in computer science for the purpose of adaptation (see Section III), we mainly narrow down our research to the Big Five model.

### B. Interpersonal Circumplex

Appraising a situation in a certain way depends not only on the personality [14], but also on the interpersonal attitude. The *Interpersonal Circumplex* [15]–[17] depicts this stance towards other individuals using the following dimensions:

- **Dominance:** Vertically ranging from *submissive* to *dominant*, this axis shows a person's disposition to behave according to their own interests. It is also called *status* or *agency*.
- **Friendliness:** This horizontally oriented axis describes how much a person cares about others and evaluates them positively. It ranges from *cold* to *warm* and is also called *affiliation* or *communion*.

According to literature, these axes are connected to the personality traits agreeableness and extraversion [15], [17]. Both traits can be located in the circumplex by rotating 30-45° relative to the dominance and friendliness axis (see figure 1)

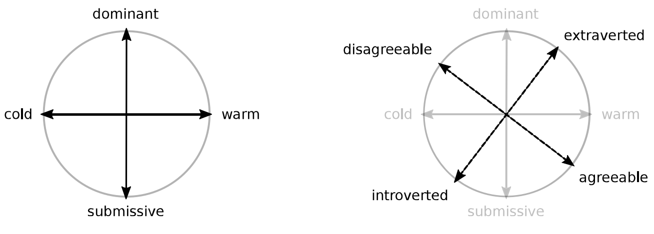


Fig. 1. Scales defining the Interpersonal Circumplex. *Solid:* Dominance and Friendliness. *Dashed:* Extraversion and Agreeableness.

### C. Interpersonal Compatibility

*1) Similarity Attraction:* One theory about compatibility is that people prefer interacting with those of similar personality and interpersonal attitudes ("birds of a feather flock together") [18]. For example, Moon showed that people perceived a computer system as having a higher expertise when the information was presented in a manner matching the user's own dominance [19]. Dominant users were also more likely to change their ranking of different cars when the computer contradicted them in a dominant manner, using direct commands and assertions rather than questions and suggestions. Andrist et al. later showed that people were more motivated to solve a puzzle task with a robot whose gaze behavior expressed an extraversion level similar to their own [20]. Similarly the idea of being equal is stated by Higgins [21]. He suggests that regulatory fit within the regulatory-focus theory should match the promotion- or prevention-focus of the user, which results in an increased engagement for a task.

*2) Complementary Attraction:* Another theory states that people are more compatible with those whose traits compensate for shortcomings in their own ones ("opposites attract"). This does not necessarily apply to all traits, but rather a specific combination of them. For instance, Markey et al. examined how dyads of strangers behaved during their first encounter, collaborative and competitive tasks [22]. They found that behaviors tended to trigger reactions similar in affiliation but opposite in dominance. Liew and Tan found that students experienced stronger motivation and more positive emotions when combined with a tutoring agent of the opposite extraversion level [23]. Introverted students rated a learning environment more positively when faced with an extraverted agent, while extraverted students liked the introverted agent more and tended more to trust it.

*3) Goal directed Attraction:* Other researchers have attempted to explain compatibility in a way that reconciles these two conflicting theories. Tett and Murphy observed that people preferred co-workers who allowed them to express their own personality traits [24]. Similarity is therefore preferred in agreeableness or affiliation because it allows both people to express closeness. In contrast, dominance is best expressed when both people agree on who is the leader and who is the submissive one. Reisz et al. examined how a person's goals and motivations may be related to their personality [25]. They observed that, in general, people either try to compensate for a negative personality trait or seek out experiences in line with their positive traits. For example, an introverted person may have goals to be less shy and more social, while an open-minded person may have the goal to learn a new skill. These observations might explain why agreeable people seek out similar personalities, reducing the risk of conflicts, while some introverts may become friends with extraverted individuals whose outgoing nature helps the former to meet new people as well.

## III. Personality Adaptation System

As already stated in section II the findings from psychology are usually used to be applied to embodied agents. This results in the need for adapting the personality of the agent to one of the attraction theories in order to endow it with a compelling personality. Shaping the personality of an agent consists mainly of two subtasks. Since personality during interpersonal interaction is conveyed i.a. by social signals, the traits should be mapped to observable cues. Additionally, the assigned communication style has to be adapted over time in order to match the user's desired personality.

### A. Conveying Personality

Personality can be conveyed by expressing the corresponding cues through different modalities. Virtual and embodied agents usually apply findings from human communication research, which result in expressing personality in terms of linguistic, prosodic, postural, gestural, gazing and turn-taking cues. While not being a problem for virtual agents, some of today's social robots still have limited movement capabilities due to hardware or software constraints. However, a flexible animation API is beneficial for implementing expressive and convincing multimodal robot communication [26].

**Linguistics/Prosody:** In terms of linguistics, personality can be expressed through the content and style of utterances. Moon and Nass [27] use language based cues (e.g., weak vs strong language) and confidence levels (e.g., low vs high) to convey different degrees of dominance in a computer-based environment. The PERSONAGE system of Mairesse and Walker [28] is able to generate natural language shaped to the desired Big-Five personality profile in a restaurant comparison scenario. This system is used among others to train a neural network generating text containing the corresponding linguistic style [29]. An additional task-oriented neural network generating method with a variable degree and improved control of expressed personality is proposed by Harrison et al. [30]. A similar approach generating natural language with a variable degree of extraversion in a robotic storytelling scenario is implemented by Ritschel et al. [31].

Applying the appropriate prosody to speech is crucial for conveying the actual meaning of spoken language and communicating the intentions in the desired way. It can be also an important communication channel to convey personality. According to Reeves and Nass [4] synthesized voices are perceived as more extraverted, when a higher pitch, wider pitch range, louder volume and faster speech rate are used. For introverted voices the opposite instantiation of the corresponding cues is used.

**Posture/Gesture:** Additional important communication channels for expressing personality are postures and gestures. Ibister and Nass [32] use a virtual character and suggest to communicate higher extraversion with spread limbs, higher range of movement and directing gestures towards the listening interlocutors. In contrast, introverted behavior is shown by holding limbs close to the body and using less open gestures. Neff et al. [33] codes these behaviors into several parameters and uses them to configure a virtual agent.

**Gaze:** The style of gazing can influence the personality perception of an interlocutor. Extraverts tend to i.a. use longer gaze while listening [34]. Transferring these kind of cues to virtual agents, Bee et al. [35] suggest that the expressed level of dominance depends on the gazing direction in combination with the head orientation. According to other findings from Arellano et al. [36], virtual agents are perceived as more extraverted and less agreeable when they turn their head upwards.

**Other communication channels:** There is the possibility to convey personality beyond traditional human communication modalities. For example, Ritschel et al. [37] successfully adapted nonverbal sounds to express emotions and intentions for a robotic puppet, which is also of high interest for shaping an artificial agent's personality. Faur et al. [38] endow an agent with machine-learning based board game strategies. Theses strategies are used to express personality through the thereby learned regulatory-focus.

According to Janowski and André [39], the turn-taking style can be used to convey personality. Intraversion and submissiveness is shown by allowing interruptions and a later starting point for speaking. In contrast, interrupting interlocutors and speaking over them is perceived as extraverted and dominant. Gebhard et al. [40] confirmed that similar relationships between speech timing and personality are found in an interactive human-agent setup.

### B. Adapting Personality

Proceeding from the personality attraction theories of section II-C the interaction quality is influenced by applying situationally appropriate personalities. To be positively perceived the profile of the agent should be appropriate with respect to the user's personality or be aligned according to interactional roles of the interlocutors, resulting in different user preferences for personality profiles. To address the variety of task contexts, their different requirements, to match the individual user's preferences and to be able to adapt to changes over time, the personality of an agent can be adapted to express a certain personality matching individual user preferences. An overview on different ways to achieve this can be seen in figure 2.

One way to accomplish personality adaptation is to explicitly program the agents personality according to one of the attraction theories (see similarity attraction or complementary theory in section II-C). However this requires knowledge about the actual personality of the user. One approach to achieve this is collecting human input by filling out for example a questionnaire or a personality report to assess his own profile. This can be done explicitly before and during interactions. For task-oriented interactions this can also be done implicitly during the interaction.

Another approach to adapt an agent's personality is to tweak the parameters during the interaction to implicitly approximate that of the user. To this end, the human input is collected online during interaction and usually is retrieved by a realtime social signal processing approach. These approaches use to predict the personality of the user according to his implicit input regarding speech, gestures, pose, facial expressions and more. Carbonneau et al. [41] for example use features and spectrograms to approximate personality from speech. Salam et al. [42] otherwise estimate the big five personality traits fully automatically by observing nonverbal behavior cues. However, the signal processing approach is not restricted to personality cues. It can also be used to

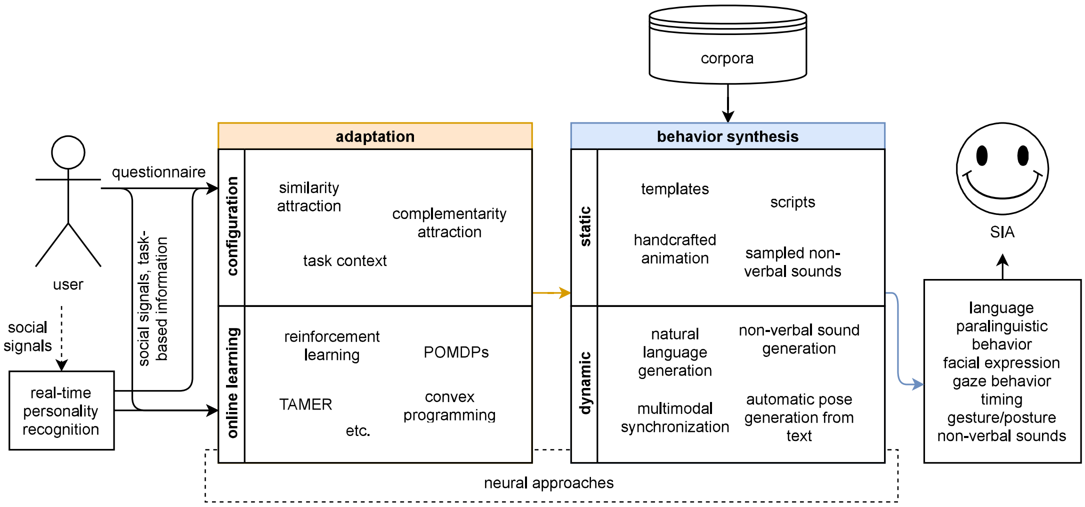


Fig. 2. Architecture of a socially interactive agent system adapting its personality to the user's preferences.

estimate user variables, that are related to personality traits. According to the literature [42], [43] human engagement is related to personality. Hence this information can also be used to adapt an agent's behavioral style. Ritschel et al. [31] and Ritschel and André [44] for example used this to manipulate a robot's extraversion degree. According to Mancini et al. [45], engagement can also help to adapt the warmth and competence of an agent.

*1) Socially-Aware Reinforcement Learning:* As depicted in figure 2, reinforcement learning can be used i.a. for adapting the personality of an agent during interaction.

In traditional reinforcement learning, a system called agent learns stepwise via trial and error to take appropriate actions in different situations. In contrast to supervised learning the agent has no expert labels and entirely learns from environmental feedback gathered at each step during runtime. Because the optimal actions are not evident from the beginning, one of the main challenges for the action selection in each step is negotiating a compromise between exploration (taking possibly suboptimal actions regarding the agent's current experience) and exploitation (taking most profitable seeming actions).

One possibility to represent the different situations and rewards of the control problem in a human-agent interaction is to explicitly provide feedback. This can stem from haptic keystroke ratings [46], graphical user interfaces [47], tactile [48], [49] or paralinguistic input [50]. However, requesting constantly explicit information can become very tiring over a longer period of time and can additionally destroy the immersion, which biases the input.

A more unobtrusive way of gathering the information for the social agent would be to collect it implicitly. Hereby the input is retrieved unconsciously from the user by observing social signals, bio signals or task related information. The latter one is crucial for predicting the user's performance in games, exercises or goal oriented tasks, as shown by [51]–[53]. However this type of data lacks information about human traits like behavior, mood or personality of the user. Thus, different scenarios use laughter [54]–[57], interaction distance, gaze and smile [58]–[61], motion speed, timing [62] or gesture and posture [31], [63] as feedback to the adapting agent. To account for physiological feedback also electrocardiography electrocardiography (ECG) [64] or electroencephalography (EEG) [65] can be collected. Usually there is a demand on gathering and combining data to a user model, which can be used to shape the reward. This can i.a. be used to estimate human emotion [59], [60], [66], curiosity [58], engagement [31], [45], [67] and fun [57], [68].

The traditional reinforcement learning approach previously described has been extended in multiple works [31], [67], [68] to Socially-Aware Reinforcement Learning. This is implemented by encoding implicitly gathered social information into the different RL components (e.g., situations, rewards). This enables the agent to unobtrusively adapt the personality during interaction, however there are also a few challenges.

For instance Martins [69] emphasizes the demand of a more detailed psychological understanding of the user to conduct experiments. This way the satisfaction and acceptance for social robots are expected to increase while using psychological measures like personality.

Under non-changing circumstances, such as preferences for moral standards or ethical values, a stationary algorithm may be sufficient. However, human preferences may change spontaneously, leading to a stationary algorithm perform worse. Hence, in this case it is crucial to also consider non-stationary algorithms, which use a constant small learning rate. This steers the impact of new feedback to the change of the learned policy and therefore how fast an agents adjusts its knowledge to new human preferences.

*2) Neural Networks:* In contrast to the stepwise online adaptation approach of the Socially-Aware Reinforcement

Learning, personality expressing behavior can also be realized during interaction by using a data-driven method. As depicted in figure 2, neural networks can be also used to adapt the personality. Therefore networks are usually trained on large corpora in a supervised manner to assemble different speaking and nonverbal behavior styles.

A chatbot with an individual personality was created by Nguyen et al. [70] training a neural network to map utterances from famous sitcom personalities to chatbot responses. In order to predict the chatbot's answer from the user's utterances they made use of a encoder-decoder architecture, where the decoder processes the user input and the encoder returns the answer. The sequence-to-sequence model has been able to adapt certain linguistic styles which are linked to personality. However, this approach can't deal with semantic content of utterances, which is crucial for task-based scenarios.

This shortcoming is addressed by Oraby et al. [71], who train a neural network considering both the linguistic variation and semantic aspects. Therefore they assembled a large training dataset of task-oriented utterances from the restaurant recommendation domain, which vary their personality according to three different profiles using the PERSONAGE generator of Mairesse and Walker [28]. Their evaluation revealed that the learning of linguistic style in a goal-oriented environment using sequence-to-sequence based neural networks is a promising approach.

In contrast to the previous approaches, Hoegen et al. [72] are not directly using personality style as input. They realize a neural network based chatbot using a predefined conversational style with respect to input variables like pronoun usage and speech rate. Matching this linguistic style can also be interpreted as an adaptation process since interlocutors use to match their conversational style to the other conversational partners [73]. Although there is no explicit mapping between linguistic styles and personality traits, there are cues with a clear connection to personality, for instance the utterance length and speech volume show a clear connection to extraversion.

Similarly [74]–[76] use the conversation style of the user as input and adapt the prosodic behavior accordingly.

Neural networks can also be used to adapt the behavior style of character animations. Smith et al. [77] transfer the style regarding the timing, foot and pose in realtime using neural networks. This approach is combining heterogenous actions and motion sequences needed to get adequate quality animations resulting in the benefit of a smaller dataset.

## IV. Conclusion

For implementing a compelling and engaging interaction, it is crucial to endow an agent with a personality that is approximating the user preferences. As previously shown, this is based on psychological findings about different attraction theories (similarity, complementary, goal-directed) and has to be evolved towards the preferred personality profile. To enable the adaptation explicitly and implicitly, human input is passed to the adaptation component. For the adaptation mechanism, Socially-Aware Reinforcement Learning and neural network based approaches were presented. To express the current personality, linguistic, prosodic, postural, gestural, gaze-related, turn-taking-based and nonverbal sound related communication channels are used to convey the personality cues during interaction. Since humans tend to attribute human characteristics to technical systems, they interpret the expressed personality cues in a human way.

Concerning future systems, simple heuristics and mere mimicking will not be sufficient for a personality adapting agent. The underlying psychological foundation has to be explored more deeply and their findings have to be taken into account. This will enable a more socially competent system in a bigger range of scenarios. Additionally, the systems have to develop towards a more automated direction, where probabilistic models will predict the preferences more precisely in various contexts. Retrieving the expected utility or reward from the chosen action can then serve as an input to choose the optimal interaction strategy.

To become even more convincing, the understanding of the bidirectional dependency of personality and emotions also have to be deepened. Adapting the agent's personality to the user preferences is just one part of this complex interrelation. Assuming a specific personality of the user, this refers to how the agent will express the personality cues after one adaptation step and how this will influence the emotion perception by the user. Since personality also determines the agent's way of expressing emotions, these communicated emotions would also contribute to affect the resulting user emotions.


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