D4.1 Interim Report on Non-verbal Agent Behaviour Enabling

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Reply to	thomas.kiderle@informatik.uni-augsburg.de silvan.mertes@informatik.uni-augsburg.de
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Author(s)	Thomas Kiderle, Silvan Mertes, Hannes Ritschel, Kathrin Janowski, Elisabeth André
EC Project Officer	Ms. Adelina Cornelia DINU - Adelina-Cornelia.DINU@ec.europa.eu
Abstract	Equipping the PRESENT agent with natural and engaging communication abilities is a challenging task. This encompasses among others the ability to show empathy within the conversation, the intelligence of adapting the behaviour style with respect to verbal, paralinguistic and nonverbal aspects focusing on the user preferences and the skill to communicate with an appropriately emotionally coloured voice. In order to realize this desired communicational intelligence the skills of the PRESENT agent will be motivated by the psychological research investigating interpersonal communication. In this deliverable, we describe our efforts conducted in the first period of the project to provide the PRESENT agent with the necessary non-verbal behaviour to be positively perceived as a sentient being during interaction with the user regarding the mentioned behaviour styles.
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1 Executive Summary

Equipping the PRESENT agent with natural and engaging communication abilities is a challenging task. This encompasses among others the ability to show empathy within the conversation, the intelligence of adapting the behaviour style with respect to verbal, paralinguistic and nonverbal aspects focusing on the user preferences and the skill to communicate with an appropriately emotionally coloured voice. In order to realize this desired communicational intelligence the skills of the PRESENT agent will be motivated by the psychological research investigating interpersonal communication.

In this deliverable, we describe our efforts conducted in the first period of the project to provide the PRESENT agent with the necessary non-verbal behaviour to be positively perceived as a sentient being during interaction with the user regarding the mentioned behaviour styles.

2 Background

The deliverable at hand reports first advances made in WP4 in terms of enhancing the nonverbal behavior of the PRESENT agent and the user focused agent adaption.

The document is a year one, second quarter deliverable, and its main function is to report about the defined nonverbal behavior improving the quality of human-agent interaction and implemented components addressing this goal. As a result ideas for implementation of empathy calculation, the implementation of a Socially-Aware reinforcement learning system for personality adaption and a GAN-system for voice conversion will be described.

3 Introduction

Intelligent virtual systems, may they be just voice-based or embodied ones, are expected to increasingly become part of our daily life. Endowing these agents with a convincing personality is an important step in establishing and maintaining a human-machine relationship (Breazeal, 2004). This helps building trust, motivating to solve tasks and promoting continuous usage, even after the novelty effect decayed.

To achieve this goal we identified three different areas, which tweak the personality of the agent to a more natural one. The first area will give the agent the ability to show empathy during the interaction by inferring an internal emotional state. This will be crucial for appearing more trustworthy and caring (Niewiadomski et al., 2008).

The second social aware mechanism concerns the adaption of the personality itself. This can be a quite complex task, because the personality preferences often vary because of different aspects. One issue is the demographic background of a person, which may have an impact on the perception of given phrases. In this context the latter one can either be seen as polite or convincing (Hammer et al., 2016). Others can prefer similar or opposing personality traits depending on the own personality (Bernier and Scassellati, 2010; Bickmore and Cassell, 2005). Moreover other researchers state that the preference of an equal or opposite personality originates from the task context (Joosse et al., 2013). According to these results there is no overall theory of personality adaption, so it will be necessary for an effective and emotionally binding interaction, that a virtual agent adapts its behaviour dynamically to the user's personality preferences. Adapting the personality to the user preferences and the surrounding task is crucial for the agent to be accepted and its natural appearance (Laurel, 1997). Aly and Tapus (Aly and Tapus, 2016) additionally found out that adapting a robot's personality to the human contributes in the engagement of the interaction.

Our third area of social adaption concerns the colouring of the agent's voice. Not only verbal and nonverbal cues, but also and sometimes especially the emotional colouring of the voice contributes to a more natural interaction.

The remaining sections are organized as follows:

This deliverable addresses the design and implementation of a convincing personality for the agent. Therefor positive behavioural traits will be defined. In section 4.1 first psychological background knowledge will be introduced. Based on this section 4.2 addresses the calculation of the internal emotional state for showing empathetic behaviour. The following section 4.3 encompasses a description of our realized Socially-Aware Reinforcement Learning framework, its usage in personality adaption and the plan for adapting the agents personality trait extraversion. In section 4.4 our GAN and CycleGAN approaches will be depicted, which are applied for the emotional voice adaption. Section 5 shows a road map for the planned enhancements of the PRESENT agent. Finally section 6 summarizes the deliverable.

4 Nonverbal Agent Behaviour Enabling

Enhancing the quality of communication between an agent and a user requires knowledge about relevant psychological theories. The concerning background will be introduced in the next chapter. Based on this we will discuss, how we decided to improve the human-agent interaction. Therefore, we present in the following chapters adaption mechanisms for an internal emotion calculation, personality adaption and emotional voice conversion. For a comprehensive overview on the implementation of adaptive personalities and the underlying psychological theories and concepts, we refer to a recent Present article (Janowski et al., 2021) to be published very soon.

4.1 Psychological Theories

To be computationally able to work with the personality of the agent or the user, it is first necessary to quantify the abstract concept. The psychological literature provides a number of established models defining personality and associated interpersonal relationships. Several of these have been successfully used in human-computer interactions and will be introduced in the next chapter. Additionally, the psychology offers a couple of theories which address the interpersonal compatibility and preference of individual personality attributes. Since these theories are based on personality they will be presented in a subsequent section.

4.1.1 Personality and interpersonal attitude

"Personality" is associated with behaviour patterns in various contexts, where an individual has tendencies to react willingly in a certain way encountering a certain situation (Argyle and Little, 1972). It will be reflected in their interpersonal behaviour, since as explained in this chapter the personality and interpersonal attitude models are interconnected with respect to several aspects.

4.1.1.1 Five Factor Model

The Five Factor Model is probably one of the most popular and widely spread frameworks for describing the abstract concept personality. It is also known as the Big Five (McCrae and John, 1992; Mehrabian, 1996a). This model describes personality in terms of the following five dimensions, commonly abbreviated by all first letters to OCEAN:

1. **O**penness**:** This attribute is described by creativity, intellectuality and curiosity. People characterized with a high openness are more open-minded. So they think unconventionally and have a wide scope of interests. Differently people with a low openness are more close minded, which is related to be more conservatively and unimaginative.
2. **C**onscientiousness**:** This personality trait is associated with a sense of discipline and responsibility. Highly conscientious people are usually reliably, dutiful, thorough and well-organized, which result in an efficient and productive behaviour. Lower conscientiousness leads to a lazy and indulgent acting style.

3. **E**xtraversion**:** The extraversion characteristic is connected with assertive and expressive behaviour. People with a high degree of extraversion are more communicative, active, expressive and gregarious than introverted ones. The latter ones are characterized to be more quiet, passive, shy and reserved
4. **A**greeableness: The personality trait is connected with getting along well with other people. Hence a high degree of agreeableness includes kind, compassionate, forgiving, trusting and generous behaviour. Low agreeable people are perceived to be cold-hearted, inconsiderate and they tend to criticize others.
5. **N**euroticism: Another commonly-known word for this factor is emotional stability. A personality with a high degree of neuroticism is related with the tendency to perceive negative affects like anxiety or distress. Additionally, neurotically people show quick, frequent mood changes and feature an impulsive behaviour. In contrast emotional stability is characterized by being more relaxed and calm.

4.1.1.2 PAD Model

A person's generally tendency for individual behaviour can be alternatively derived from the PAD Temperament Model known as Pleasure-Arousal-Dominance-Model (Mehrabian, 1996b). This model is dimensional and defines the following three axes associated to the Big Five personality traits (Mehrabian, 1996a):

- **P**leasure: This axis corelates with a person's tendency to perceive positive affective states. According to Mehrabian this is quantified by:

$$0.21 \times \mathrm{Extraversion} + 0.59 \times Agreeableness - 0.19 \times \ \mathrm{Neuroticism}$$

- **A**rousal: This attribute defines how responsive an individual reacts with respect to stimuli. Additionally, it indicates the time for the person to calm down. This trait is calculated by:

$$0.15 \times \mathrm{Openess} + 0.30 \times Agreeableness + \ 0.57 \times \ \mathrm{Neuroticism}$$

- **D**ominance: The personality trait dominance reveals the degree to which a person feels to have the control of their own actions. The following formula translates this trait to numbers:

$$0.25 \times \mathrm{Openess} + 0.17 \times Conscientiousness + \ 0.60 \times \ \mathrm{Extraversion} \\ - 0.32 \times \ \mathrm{Agreeableness}$$

Alternatively, to the modeling of personality those three axes are also used to describe the affective states of a character in a human-agent-interaction. This includes the short-term emotions and long-term mood. This usage is possible, because the concepts depend on and impact each other (Gebhard, 2007). Since personality, mood and emotions all contribute in shaping an agent's behaviour at a certain point in time, it's crucial to define a common framework for a consistent system behaviour.

4.1.1.3 Interpersonal circumplex

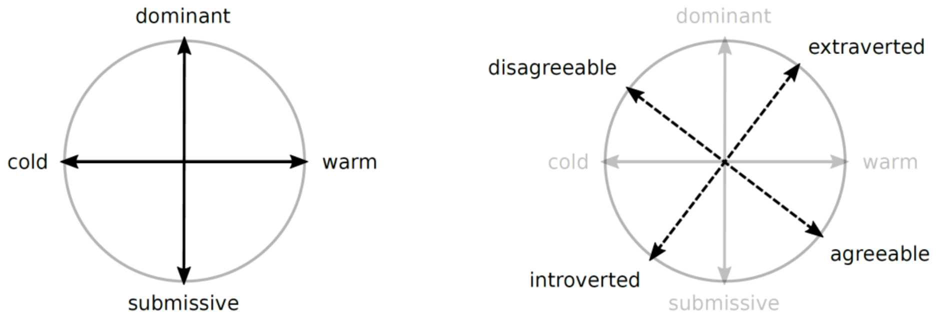


Figure 1: Interpersonal circumplex which is defined dimensionally (left, solid: status and affiliation - right, dashed: extraversion and agreeableness)

In human-agent-interactions it's also crucial to model interpersonal attitudes. For encoding stances towards interlocutors normally the Interpersonal Circumplex is used (McCrae and Costa, 1989; Horowitz et al., 2006; DeYoung et al., 2013). Thereby another two axes are defined:

- Status/Agency: This dimension is usually depicted vertically and encompasses attitudes ranging from submissive to dominant. The axis describes the tendency of people to follow their own will.
- Affiliation/Communion: This axis is most of the time placed horizontally and ranges from cold to warm. This shows the closeness of a person to other humans.

According to the literature both axes can be interrelated with the personality traits extraversion and agreeableness (McCrae and Costa, 1989; DeYoung et al., 2013). In this case this alternate axis pair is positioned 30-45 relative to the status-affiliation pair (see Figure ***1***).

4.1.2 Interpersonal Compatibility

One of the two main theories about interpersonal agreeableness is the similarity attraction theory. It suggests that people with similar personalities would be more compatible ("birds of a feather flock together") than dissimilar people. The second main theory assumes the opposite. According to this complementarity theory people with dissimilar personalities are more compatible ("opposites attract"). Sometimes the personality attraction depends on the underlying goals, which shape the behaviour of two persons and the appraisal of individual events. In this case both main theories about personality attraction must be combined into new approaches.

4.1.2.1 Similarity Attraction Theory

The attractiveness regarding similarity is commonly studied in terms of interpersonal stances, but similar effects have also been found for personality traits (Montoya and Horton, 2013).
Moon (Moon, 2002) investigated how the dominance of a study participant interacting with the corresponding system influences the persuasiveness of computer-generated messages. This experiment showed that dominant users tended to vote for a higher information quality and to change their car rating more often if the computer contradicted in a dominant way. If the user's personality matched with respect to the dominance of the computer, the digital interlocutor was attributed a higher level of expertise.
Another experiment demonstrated that the presentation style of music, cartoons and health tips was preferred in case of matching the dominance level of the user. Moon and Nass (Moon and Nass, 1996) similarly showed that people were attracted to computers which adapted their dominance increasingly to the user over time. Computers with a remaining or in an opposing way developing dominance level were not rated that attractive.
Andrist et al. (Andrist et al., 2015) altered the gazing style of a robot to express an introverted or extraverted behaviour. They conducted an experiment, where people had to solve a puzzle task with the robot and let the subjects decide on the duration of the puzzling. It turned out, that people without own motivation to solve the puzzle and a similar extraversion degree spent more time with the robot than participants with a different personality. Thus, they decided to solve more puzzle tasks.

4.1.2.2 Complementary Theory

Behaviour that reflects a particular combination of status and affiliation is called complementary (Estroff and Nowicki Jr., 1992; Markey et al., 2003).

Markey et al. (Markey et al., 2003) observed unknown dyads and their behaviour during encounter, collaborative and competitive interaction. Their observations confirmed that behaviours triggered similar responses in terms of affiliation but opposite ones in terms of status.
Estroff et al. (Estroff and Nowicki Jr., 1992) investigated whether complementary people performed better in a puzzling or word searching task opposed to anti-complementary dyads. In their definition complementary individuals are similar in affiliation, but opposite in status. The values are switched for anti-complementary pairs. The experiment revealed a better puzzling performance for complementary people, which counts also not significantly for the word searching.
Shea and others (Shea et al., 2013) showed that low self-control leads people to be more sensitive to this trait in others than their counterparts with high self-control. Additionally, participants with low self-control sense a greater difference regarding competence and rated the ones with high self-control to be more favourable. Also in romantic relationships, individuals with low self-control and a no-self-control partner feel a higher level of dependence.
Liew and Tan (Liew and Tan, 2016) observed students in human-computer interactions, which had more positive affective states and learning motivation during an interaction with a virtual tutoring system having the opposite extraversion degree of the corresponding student. Additionally, the students with high extraversion assessed the introverted agent to be more engaging and trusting.

4.1.2.3 Interpersonal Goals

Neither the similarity nor the complementarity attraction theory is universal, so other researchers have focused on the interaction goals and the underlying personal motivations to explain the interpersonal attraction.
Tett and Murphy (Tett and Murphy, 2002) suggested that "people prefer employees who let them be themselves" which would explain both the similarity and the complementarity attraction. According to their findings the expression of personality is a basic human need. In some cases, people want to show agreeableness and affiliation to express mutual closeness. In other cases, dominance has to be shown because one wants to lead and the other wants to follow. For expressing the interpersonal closeness a similar, for showing dominance a complementary personality is preferred.
Horowitz and others (Horowitz et al., 2006) found that a person's goal the status or affiliation may be interrelated, whereby frustration occurs when the goal is interpreted in a wrong way. For example, a person can discuss a problem by asking for advice or comfort. The former one is motivated by status, the latter one by affiliation. If the seeking person is getting something different he expected, the interaction will be terminated.
Reisz et al. (Reisz et al., 2013) investigated how personality traits and personal goals are interrelated.
According to their findings, people define objectives leading to a positive or compensate a negative effect. This applies particularly for time-consuming goals. As an example people with high openness aim to learn new skills, while introverted people pursue the goal of making new friends. People being low conscientious aim for goals like “use time more efficient”. High conscientious and neurotic people set goals like “reducing stress”. According to these results two individuals are compatible when they enhance their positive traits. This is for example the case if two friends have a high agreeableness. On the other hand compatibility can also be implied by a person compensating for a trait deficit of another one (e.g. an introverted makes extraverted friends).

4.2 Internal Affective State Calculation

One crucial way to enhance the quality of a human-agent-interaction is to endow the system with emotional behaviour. However, to express affective states consciously or subconsciously an agent needs to “know” before in which emotional state he is. So a mechanism is required, from which the affective state can be deduced and retrieved. The following chapters introduce conceptual ideas of a new emotional state calculation approach, which will include different internal and external contextual components. First the required affective elements are described. In another section the conceptual ideas of the approach itself will be depicted.

4.2.1 Affective elements

In our emotional state calculation method, we use the affective elements personality, mood and emotion, which will play a role in showing emotional empathetic behaviour. Therefore, these affective concepts will be explained shortly:

- **Personality**: This affective element specifies general aspects of the agent's behaviour in a long-term way. We plan the integration of the Big Five Model (see chapter 4.1.1.1) to define all personality traits, which will influence the emerging emotions and therefore the resulting mood.

- **Mood**: This is a middle-term affective element, which reflects multiple subjective emotions in reaction to a couple of events. Compared to emotions it is more stable over a longer period of time and has therefore more influence on the affective behaviour of the agent. Presumably the agent's and the user's mood will be defined by Russel's circumplex (Russell and Barrett, 1999), which encompasses the valence and arousal dimensions.

- **Emotions**: In contrast to personality and mood these are short-term affective elements, which arise in response to a specific event. They inherently carry an intense feedback referencing to a short period and decay over time. In our concept for the computation of an internal affective state we focused on the specific emotions anger, upset and boredom. An emotional state for the agent and the user will be realized by Russels emotional circumplex (Russell and Barrett, 1999).

- **Empathy**: Affective states of other individuals can elicit an emotional reaction from individuals. This affective response is generally considered as empathy. Blair et al. (Blair, 2005) is distinguishing three empathy types. The first one is called motor empathy and enables an interlocutor to become emotionally aroused as a response to an observed emotion and imitate it. The second one, affective empathy, makes the interlocutor care for other's well-being. The last one makes cognitive empathetic people imagine emotions and accept the mental perspective of others.
  We'll focus on motor empathy and therefore on enabling the agent to detect the affective states of the user. To show an empathetic behaviour as a response to this observations he also has to imitate the emotions of the user. As a result this has to be reflected first in the elicited emotions and followed by an updated mood state of the agent.

4.2.2 Emotion Calculation Model

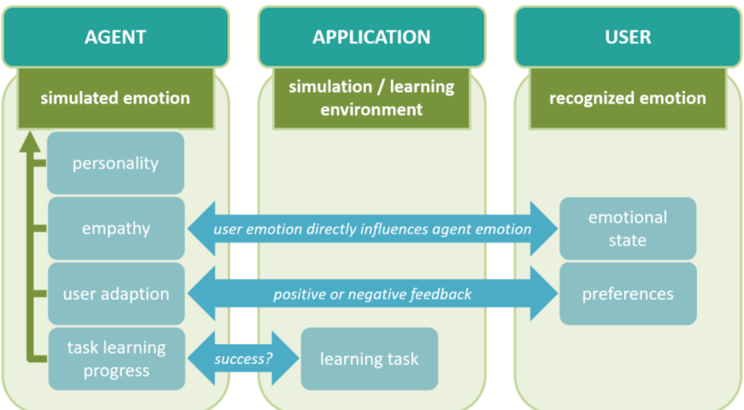


Figure 2: Approach for internal affective state calculation

We developed ideas of a conceptual emotion calculation process. The latter one is shown in Figure 2, where the simulated emotions and a resulting mood are calculated. Both are influenced by different factors in the calculation process, these will be described in the following.

Before the calculation process starts several parameters concerning the agent have to be defined. All of them won't change during the whole procedure. First the five personality traits from the Five-Factor model must be defined. As stated above this will have an effect on the emerging emotions. For showing empathy it's also important to which degree the emotional states of the interlocutor (in this case the user) influence the own affective state. Therefor an empathy parameter is defined.
In the calculation process itself the autonomous agent is supposed to solve a certain decision making task through a Socially-Aware machine learning algorithm, which will be described in detail in chapter 4.3.2.2. To implement the Socially-Awareness it is necessary to recognize the emotions from the user applying the valence-arousal circumplex from Russel (for details see deliverable 4.2). This returns an emotional state of the user. Additionally, the machine learning algorithm provides a reward for the last action of the agent. Beyond this feedback also information about the adaption progress is on-hand.

The combination of the recognized user emotions, the learning feedback and the task progress will contribute to the emotion elicitation. As a result and under certain conditions the agent can be angry, upset and bored. Let's say for example the agent fails in supporting the user over a longer period of time then he might get upset. Considering the emphathy parameter each evoked emotion contributes in pushing the agent's mood towards the corresponding direction of the valence-arousal space. This way both the emotions of one time step and the mood of the agent become available as an affective state. This will be used to emotionally steer the verbal, paralinguistic and nonverbal behaviour of the agent.

4.2.3 Next steps

The depicted emotion state calculation is actually just on a conceptual basis. So, a next step will be the implementation of the presented emotion calculation approach. Since this affective state calculation and the user-focused adaption from chapter 4.3.2.2 both require social signals from the user, another next step will be the integration of the social signal recognition component of deliverable 4.2. Additionally, information about the learning task progress and the adaption performance of the agent is crucial for inferring the internal emotions. So a next step will be the integration of the reinforcement learning component described in chapter 4.3.2.44.3.

4.3 User-focused Agent adaption

Humans use nonverbal behaviour to establish rapport and engagement. This can help to induce an emotional bond and has a positive influence on the quality of interactions. One way to generate a positively perceived connection with the user is the adaption of his personality to the user. Since every personality has its own associated behaviour, this adaption process includes also the shaping of an individual nonverbal behaviour.
For an implementation of this process first the ingredients of personality adaption systems must be understood, there are two main goals: One is to develop an adaptation mechanism and the other is to map between personality traits and observable social signals. The latter one will be first introduced, because adaptation mechanisms require an understanding of parameters that will change over time. Afterwards background knowledge about implementing an adaption system and the concrete realization in the project will be presented.

4.3.1 Expressing Personality

Due to the flexibility of current virtual agents and social robots, personality can be expressed through various communication channels. These expressions are often adapted from psychological insights into human communication as summarized by Knapp et al. (Knapp et al., 2014).
One way to show an individual personality is to use the linguistic content of expressions. In this context Moon and Nass (Moon and Nass, 1996) use predefined language clues (strong language, statements and commands to express great confidence as opposed to weaker language, questions and suggestions to show low confidence). This makes the computer appearing in a dominant or submissive manner. The natural language generator PERSONAGE by Mairesse and Walker (Mairesse and Walker, 2010) outputs different linguistic styles with respect to the dimensions of the Big Five Personalities comparing restaurants. This generator is combined with a social robot by Aly and Tapus (Aly and Tapus, 2016). Ritschel and André (Ritschel and André, 2017), Ritschel et al. (Ritschel et al., 2017) use an adaptive and generative approach to a storytelling robot with a variable degree of extraversion. Harrison et al. (Harrison et al., 2019), Hu et al. (Hu et al., 2018) present methods of neural generation with different personalities (Big Five) and improved style control for task-oriented dialogues. Paralinguistic behaviour is crucial for convincingly presenting linguistic content. Reeves et al. (Reeves and Nass, 1996) found out that synthesized voices express extraversion with a faster speaking rate, a higher pitch and volume and a wider pitch range - conversely, slower speaking rate, lower pitch and volume and a smaller pitch range - indicate introversion.

Kim and others (Kim et al., 2008) give a robot the ability to express extraversion/introversion by using the size, speed and frequency gestures. Isbister and Nass (Isbister and Nass, 2000) express this dimension in a similar way with a virtual character adopting its posture. This includes open gesturing, expansive movement and gesturing towards the interlocutor for the extraversion. Conversely, introversion is shown by keeping limbs closer to the body and using less free gestures. Generative approaches (Hartmann et al., 2005) are important to make this type of behaviour flexible without having to code and write down every detail of the interaction. With sufficient personality-related training data of the audio corpa, applications in the future may also use speech-driven gesture generation (Kucherenko *et al.*, 2020) based on deep learning. Similarily, gaze behaviour can provide clues about the personality traits and attitudes of an agent. In this context Bee and others (Bee et al., 2009) showed, that the alignment of the head and eyes of a virtual character influences the degree of shown dominance. Later, Arellano et al. (Arellano et al., 2011) found out that agents turning their head upwards were perceived as more extraverted and less agreeable than those who looked downwards.
Due to the successful personalization (Ritschel et al., 2019b) of the non-verbal sounds (Bethel and Murphy, 2008) of artificial agents expressing emotions and intentions, the generation of such sounds during runtime (Luengo et al., 2017) is of great interest to adapt the personality of socially aware agents beyond the traditional verbal and non-verbal communication channels.
Studies with embodied agents have shown that *turn-takin patterns* can also be explained in terms of their personality and interpersonal attitudes. Generally speaking at a later point in conversation and interrupting earlier are signs of an introverted and submissive character. Otherwise agents interrupting the interlocutor and continuing talking over them seem to be extraverted and dominant. Maat and others (Maat et al., 2011), by Cafaro and others (Cafaro et al., 2016) and Janowski and André (Janowski and André, 2019) confirm the relationship between personality and speaker time. According to Gebhard et al. (Gebhard et al., 2019) the same holds for an interactive conversation between human and agent.

4.3.2 Agent Adaption

One way to adapt the agent's personality is using a reinforcement learning approach, that is able to consider the social cues of the user. To understand Socially-Aware Reinforcement Learning at all one must first catch the basic concepts of general reinforcement learning. Therefor we first explain reinforcement learning itself and afterwards extend these ideas to the Socially-Aware Reinforcement Learning approach. In another section we present how personality adaption usually works and relate the corresponding ideas with reinforcement learning. In this context we give an overview of related work about adapting the agents personality with reinforcement learning. In another chapter we report about work completed so far, which builds the basis for the implementation of two conceptual prototypes. Both are presented in the next two chapters. The last section outlines our next steps.

4.3.2.1 General principles of Reinforcement Learning

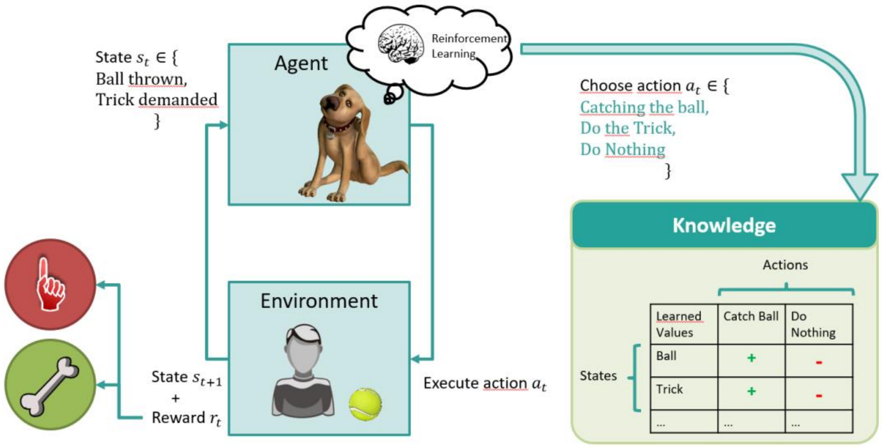


Figure 3: Basic reinforcement learning

In the basic reinforcement learning approach a system called agent learns stepwise via trial and error to take appropriate actions in different situations. Figure 3 depicts an example for a simple learning scenario. Here a dog plays the role of an agent, who has to go through all the following steps for each learning step:

First the agent perceives the owner (generally the environment) multimodally through sensors (e.g. eyes, ears) and inferences internally an environmental state. An exemplary state could be that the owner wants the dog catch a ball. The next step will be to choose an action. Since reinforcement learning solves control problems, there is a tradeoff between exploiting insofar gathered experience and exploring an action. The latter one chooses a random action according to a predefined policy and can lead to suboptimal actions, but is also crucial to find an optimal action over the learning process. Exploiting the agent's experience leads to the most profitable action according to the currently observed state and the insofar learned knowledge. After that the agent executes the chosen action and thereby influences the environment. In the example the dog would catch the ball.
Then the next learning step begins, where the agent gets a numerical reward for the previously executed action. This information gives an indication of whether the action was successful or not. For catching the ball the dog would for example get a positive reward from the owner, this could be a tasty bone. If the dog would have executed another action like doing nothing in the "catching ball"-state, he would otherwise get a negative reward in form of a rebuke. In both cases the agent accounts the with the previously gathered experience for this state-action pair. Then the process starts again for this new learning step and the dog observes a new state.

4.3.2.2 Socially-Aware Reinforcement Learning

In the interaction between the agent and the human, the feedback for the calculation of the reward can be given explicitly based on various sources of information. Explicit feedback comprises, for example, haptic keystroke ratings (Hannes Ritschel et al., 2019a), graphical user interfaces (Ferreira and Lefèvre, 2015), tactile (Barraquand and Crowley, 2008) or paralinguistic input (Kim and Scassellati, 2007). But this can become very tiring over a longer period of time and can additionally destroy the immersion, which biases the feedback. So, a more unobtrusive way getting this information has to be used.

Therefore, the learning feedback should be retrieved implicitly and not consciously given by the user. This can be derived for example from task-related information or from unconscious human bio- or social signals. Task-related data is fundamental for estimating user performance in goal-oriented tasks, exercises or games, such as Ritschel and others (Ritschel et al., 2018; Ritschel et al., 2019c; Ritschel et al., 2020). However, it cannot capture human traits like behaviour, personality or mood of the user. Thus, an appropriate interaction distance, gaze and smile (Leite et al., 2012; Gordon et al., 2016; Fournier et al., 2017; Hemminghaus and Kopp, 2017), speed of movement, timing (Mitsunaga et al., 2008), gestures and posture (Najar et al., 2016; Ritschel et al., 2017), and laughter (Hayashi et al., 2008; Knight, 2011; Katevas et al., 2015; Weber et al., 2018) are used as social feedback for agents in different scenarios. For Physiological feedback ECG (Liu et al., 2008) or EEG (Tsiakas et al., 2018) data are handled. Usually multiple signals are gathered and combined to create a user model, which will be used to calculate the reward. The latter one is for example based on estimated human emotion (Leite et al., 2012; Gordon et al., 2016; Broekens and Chetouani, 2019), engagement (Mancini et al., 2019), curiosity (Fournier et al., 2017), fun (Weber et al., 2018; Ritschel and André, 2018) and more.
In a human-agent-interaction it can be necessary to encode social information into the state calculation. Hence the state information also has to be retrieved implicitly to keep the interaction unobtrusive. This works similar to the reward.

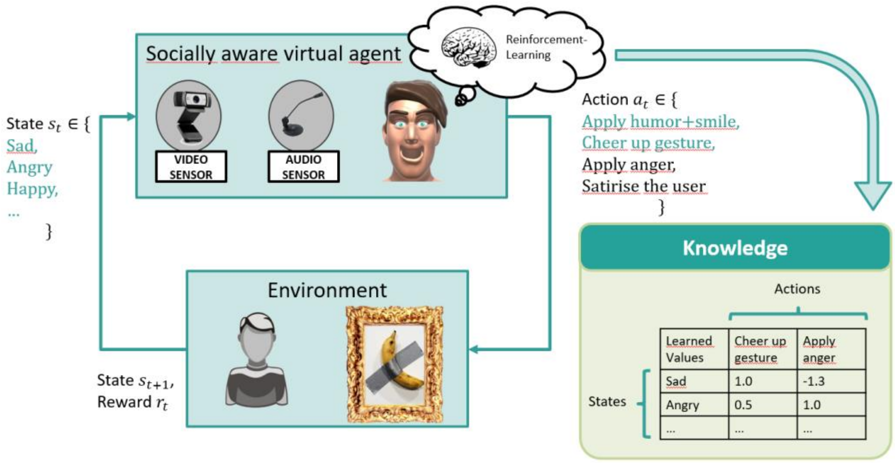


Figure 4: Socially-Aware Reinforcement Learning

Including such implicitly retrieved social information into the reinforcement learning model is a challenging task and enables the agent to be socially aware. For this reason, this learning process is called Socially-Aware Reinforcement Learning. Figure 4 depicts an example for a Socially-Aware Reinforcement Learning scenario, where the user is in an emotional state and the agents learns how to mitigate the corresponding bad emotion with an appropriate action. In conclusion, Socially-Aware Reinforcement Learning can be used to realise the user focused agent adaption considering the social aspects of the user. One application scenario for this learning approach could be for example the adaption of the agent's personality to the user.

4.3.2.3 Personality Adaption using reinforcement learning

Concerning personality, the term adaptation is used in the context of manipulating the behaviour of an agent to express a personality that is best suited to the individual user. An overview of the typical architecture for the adaption and expression of personality for an agent is depicted in Figure 5.

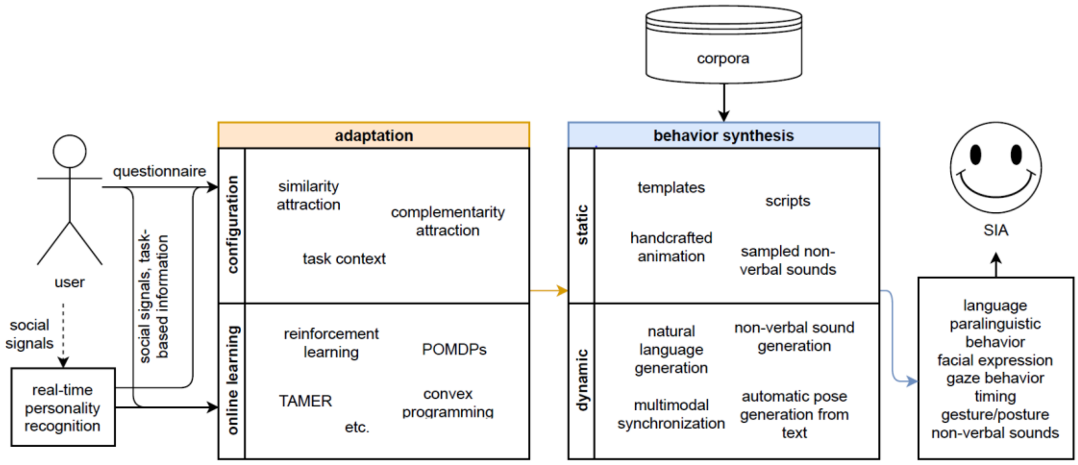


Figure 5: Adaption and behaviour synthesis for personality expression of virtual agents

The adaption is usually done either by configuring the agent's personality profile according one of the attraction theories (similarity vs complementary attraction, as described in section 4.1.2) or by adjusting the corresponding parameters during runtime. Therefore, typically human input either is available as data before the interaction or is provided online during the interaction. The former is usually done, for example, by filling out a questionnaire or a self-report to determine the user's individual personality. The second one comprises approaches for real-time processing of social cues or task-related information of the user, such as the user's effort in a goal-oriented interaction. In this context, prosody and non-verbal behaviour are used for automatic personality recognition (Vinciarelli and Mohammadi, 2014). To accomplish this human information based task the signal processing uses speech, gestures, posture, facial expressions and more. On the one hand, this can be used to get the personality profile of a person. An example for this is conducting feature learning and spectrogram analysis to determine personality through speech (Carbonneau et al., 2020). In another example, Salam et al. use a fully automated system to predict the Big Five personality traits based on non-verbal behavioural cues (Salam et al., 2017). On the other hand, the signal processing information can be done in order to obtain other information about the user. Since human engagement is related to personality (Celiktutan et al., 2017; Salam et al., 2017), this information can also be used to adapt the personality of an agent.

As depicted in Figure 5 reinforcement learning can be used as one main approach for adapting the personality of an agent. Since in the last years the interest for reinforcement learning in terms of personalization and personality adaption has grown, this seems to be a promising method and will therefor be used for personality adaption of the PRESENT agent. So far the research on this topic has developed as follows:

Numerous reinforcement learning algorithms are applied for social actor's. In its simplest version the agent learns with the help of multi-armed bandits (Leite et al., 2012), duelling bandits (Schneider and Kummert, 2020) or contextual bandits/associative search (Ritschel et al., 2019a). The best known full reinforcement learning algorithms comprise Q-Learning (Liu et al., 2008; Barraquand and Crowley, 2008; Gordon et al., 2016; Ritschel et al., 2017; Hemminghaus and Kopp, 2017; Tsiakas et al., 2018; Broekens and Chetouani, 2019) and Policy Gradient approaches (Tapus et al., 2008; Mitsunaga et al., 2008). In the context of interactive systems Pietquin (Pietquin, 2013) also outlines the application of Reverse Reinforcement Learning. By observing human experts this allows to learn the reward function. This work also shows, that the phenomenon of coadaptation is an important challenge. It arises during the adaption to the user and induces a subsequent adaption of the human to the adapted agent.

Considering personality Iida et al. (Iida et al., 1998) made a robot learn social cues associated to the personality (gaze and voice) by applying reinforcement learning. In this scenario the user is interacting with the robot in different spatial areas. Each motion induces an action of the robot and is either positively or negatively rewarded. Tapus et al. (Tapus et al., 2008) tweaks the personality of a robot during exercises in post-stroke rehabilitation therapy by using reinforcement learning. Thereby the interaction distance, speed and vocal content of the therapy robot are used to increase the user's performance. The introversion was shown through soft speech with low pitch and volume, which worked supportive in the task context. On the other hand the extraversion is expressed with a challenging speech using high pitch and volume. The number of exercises performed in a given time period shape the reward signal. A group of researchers (Martins et al., 2018) emphasize, that future adaption experiments should contain deeper psychological information of the user. This could be for example achieved by including more psychological measures like for example personality. Enhancing this area will presumably lead to a better user acceptance and more natural interaction.

4.3.2.4 User focused agent adaption

Our literature review has shown that personality adaptation is essential for the quality of interaction and the user performance in task-based environments. Hence, to enhance the interaction experience with the agent, we aim to learn the user preferences for personality traits.

The literature from chapter 4.3.2.3 shows that reinforcement learning is a promising approach for adapting the personality. Accordingly, we have implemented first a reinforcement learning framework with different algorithms. As a result we can use a k-armed Bandit and Q-Learning for a desired learning task for the user focused agent adaption.

Since we have discovered in literature that extraversion is one of the most visible personality traits (Funder and Dobroth, 1987; Riggio and Riggio, 2002), it is promising to adapt the user's extraversion. In this context, we have identified two adaptation tasks: 1) We will approximate the preferred level of extraversion. Because personality as mentioned in chapter 4.3.1 is expressed through different modalities, this will influence the extraversion, of the verbal, paralinguistic, and nonverbal cues. Thus, it is 2) additionally interesting, how many and which modalities should be used by the agent concurrently.

To solve both tasks the same knowledge about extraversion is needed. Therefore, a comprehensive research about communicating the corresponding personality trait is required. We have already conducted research and thereby compiled specific behaviour cues for the expression of extraversion from the literature. The results are presented in the tables below, which are categorized by the used modality. Additionally, a short description is given how we decided to integrate the corresponding type of cue in the future:

Verbal Cues:

Since Dialogflow is used for the communication with the user, the verbal cues will be realized within this tool. Dialogflow is a framework that was introduced by Google and allows to build and control signal flows in complex dialogs. The communication between our components and Dialogflow is realized by a WebAPI. Verbal cues will be implemented by setting various contexts, which control the development of the dialog and as a result its degree of extraversion.

Source	Introvert	Extrovert
Speaking Style	• Many words per sentence coupled with elaborated, formal, many hesitant constructions	• Few words per sentence coupled with simple, informal, few hesitant constructions

	• Many articles and negations • Many: nouns adjectives prepositions (explicit) • Low contextuality→few deictic expressions (e.g. pronouns, verbs, adverbs, interjections)	• Few articles and negations • Many verbs, adverbs, pronouns (implicit) • High contextuality→many deictic expressions (e.g. pronouns, verbs, adverbs, interjections)
Lexicon	• Few positive/many negative emotion words	• Many positive/few negative emotion words
Topic selection	• Single topic • Few self-references	• Many topics • Many self-references • many agreements+compliments • Many self-references

Table 1: Verbal cues for extraversion (Mairesse et al., 2007)

Paralinguistic cues:

The paralinguistic style of the agent will be controlled by manipulating the verbal content with the SSML and transforming the text to speech with the TTS-System Cerevoice from Cereproc. Additionally for emotional content the speech will be adapted with our GAN approach (see section 4.4 for details).

Source	Introvert	Extrovert
Speech	• Slow speech rate • Many unfilled pauses (dependend on cultures: German extraverts produce more pauses than American extraverts), hesitation + Long response latency • Low volume • Low pitch range	• High speech rate • Few unfilled pauses, hesitation + Short response latency • High volume • High pitch range
Conversational speech behaviour	• Less backchannel feedback • Waiting and listening	• More backchannel feedback • Initiating conversation

Table 2: Paralinguistic cues for extraversion (Mairesse et al., 2007)

Emotional expressivity using face and voice:

The degree of expressing facial emotions with the photorealistic agent is will be steered by interfaces, which will be developed in collaboration with the partners. For manipulating the expressivity of the voice we also decided to use our GAN approach.

Source	Introvert	Extrovert
Speech/ Facial expressions	• Low emotional expressivity	• High emotional expressivity

Table 3: Emotional expressivity cues for extraversion (Riggio and Riggio, 2002)

Gaze cues:

We decided to steer the gaze behaviour by using interfaces for the photorealistic agent, which also will be defined in consultation with the partners.

Source	Introvert	Extrovert
Gaze		• eye contact maintaining

Table 4: Gaze behavioural cues for extraversion (Michael Neff et al., 2010)

Gestural cues:

Also for expressing gestural extraversion we found cues for the photorealistic agent. In order to show extraversion appropriately and as visible as possible it is crucial to have spatial gesture interfaces and also several temporal ways for steering gestures. Interfaces for the cues will be determined after they are agreed upon the partners.

Source	Introvert	Extrovert
Gesture direction	• Inward • Many self-touches • Inward in horizontal dimension	• Outward • table plane and horizontal spreading gestures
Gesture amplitude	• narrow	• Wide range of movement/broad gestures • Ellbows, hands away from body • Legs far apart standing
Gesture rate	• Low	• Correlation: High speech rate→ high gesture rate • more movements of head, hands and legs
Gesture speed, Response time	• Slow	• Fast, quick
Gesture connection	• Low smoothness • High rhythm disturbance	• High Smoothness/fluency • Low rhythm disturbance
Body parts used		• more body emphasis: ○ more head movements ○ more parallel gestures of the hands

Table 5: Gestural cues for extraversion (Michael Neff et al., 2010)

Postural cues:

Furthermore, we investigated the potential of postural cues to convey introversion and extraversion. For steering this modality also interfaces will be defined in collaboration with the partners.

Source	Introvert	Extrovert
Body attitude	• Lean backward • Turn away • Maintain upper body (chest, limbs) in a more vertical	• Lean forward (torso) • Not turning away • Moving the upper body (chest and limbs) forward

	orientation	
Body part		• More leg lean (amitious personality) • more body emphasis: more movement of the legs (position, bouncing, shaking) and more posture shifts • use most of the body during gesturing: ○ tilt head ○ raise/errect shoulders/ *chest forward* • positive correlation: between eye contact, shoulder orientation, leg orientation, and body orientation • stand closer to others

Table 6: Postural cues for extraversion (Michael Neff et al., 2010)

As stated above we already developed reinforcement learning framework. To demonstrate its basic functionality in terms of the implemented algorithms we developed a concept for two demonstrators. To make demonstrators Socially-Aware they will require an integration of the recognition pipeline from deliverable 4.2. Both will be presented in the next two chapters.

4.3.2.5 Prototype for the reinforcement learning framework

For testing the basic functionality of our framework, we first conceptually developed an agent, which takes the role of a museum guide. In this use case the agent shows different types of pictures (e.g. landscapes, portraits) and adapts the art style during the interaction. The user preferences for certain types of pictures will be inferred first through explicit feedback (e.b. buttons) and later through social signals, so the agent will adapt the kind of pictures presented to the user. This will demonstrate, that our framework enables the agent to learn user preferences for a specific problem and considers the social feedback of the user.

4.3.2.6 Prototype for the personality adaption

We also want to demonstrate, that an agent linked to this framework can also adapt its personality. Therefor we conceptually defined a Socially-Aware reinforcement learning prototype, which can adapt its degree of extraversion.
For simplicity purposes we decided to focus first on a single modality. Since facial expressions are the most simple extraversion cue type because of the limited variety, we chose this type as a starting point. For the personality adaption task, we have defined three degrees of extraversion (weak, middle and strong). To express each emotion appropriately these three intensities of expressivity are determined as an interface for each emotion. We initially also restrict the adaption of the facial expressions on the four emotions anger, sadness, calmness and happiness. This can easily extended by integrating consecutively the other types of emotions and extraversion cues.

4.3.2.7 Next steps

One of the next steps will be to refine this knowledge about the cues for extraversion. As stated above another step will be to define interfaces for the facial, gaze, gestural and postural cues, which will be agreed upon with the partners. To test our reinforcement learning framework in terms of the basic function and the personality adaption, we will develop in another next step the prototypes described in section 4.3.2.5 and 4.3.2.6. The other modalities for the second prototype will follow in another step. In order to implement the Socially-Awareness of the prototypes we additionally have to combine the social signal sensing pipeline from deliverable 4.2 with the current reinforcement learning framework and conduct tests with it.
To realize the adaption of the extraversion degree not only the extraversion cues will be crucial, but also finding learning algorithms which are sensitive for quick behaviour changes in human-

agent interactions. Our actual reinforcement learning framework encompasses actually just a basic set of algorithms for fast prototyping. So, a next step will be conducting research about efficient learning algorithms and their integration to our learning framework. To find the most efficient one for the given use case, we also have to do research about evaluation methods and integrate them into our framework. In this way, we provide a scientifically well-founded analysis of the most efficient algorithm for our learning task.
All previous steps provide the basis to fully implement the adaption tasks concerning the extraversion degree and modality selection in another step.

4.4 Voice adaption

Another important factor that is essential for a realistic and credible agent is the voice. Vocal nuances can convey a variety of information. For the human perception of a virtual agent it is important that the colouration of the voice is consistent with the emotion to be expressed. The PRESENT project therefore investigates how the agent can be equipped with a convincing emotional voice.

4.4.1 Overview of voice adaptation component

In order to achieve the goal of a realistic sounding emotional agent, we decided to use an existing text-to-speech (TTS) system and to equip it with the ability to make generated speech sound emotional. The TTS component itself, i.e. the part that performs the conversion of textual information to audio material, was not newly developed. On the one hand, the necessary acquisition of textual semantics is not part of non-verbal behaviour, on the other hand, there are already a number of available TTS systems that produce high-quality audio material. The disadvantage of existing TTS systems, however, is the insufficient ability to make the generated speech sound emotional. Although some well-known TTS systems can be parameterized by various configuration options in such a way that they can be given a certain emotional impact by a high level of expert knowledge, we believe that these options are not sufficient to enable a completely realistic perception by the user. This is due to the fact that the parameterisable features of existing TTS systems do not have sufficient granularity and are therefore unable to represent the full range of human emotion in a convincing way.

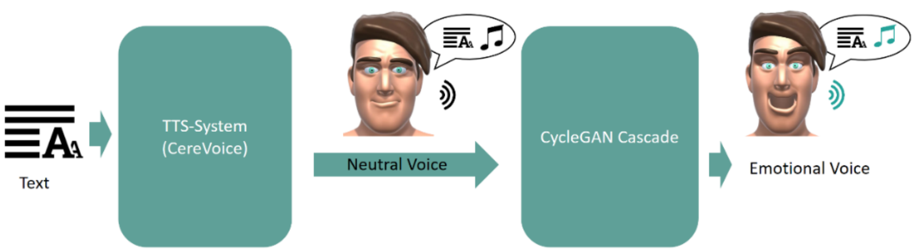


Figure 6: Emotional speech generation with GANs

For this reason, we decided to develop a component based on an existing TTS system, which uses emotionally neutral speech generated by the TTS system as input and transforms it into emotional speech. Instead of developing a procedural system based on known features, PRESENT takes the approach of using generative artificial intelligence techniques to learn a transition function from neutral speech to speech of a particular emotion. This approach avoids that too few and too rough features are used for the transformation. Instead, a deep neural network will implicitly learn the complex and multi-layered features relevant to emotional voice.

As a TTS system, the CereVoice engine of CereProc is used, as our group has already gained extensive experience with this system in past projects, and it has already proven to be suitable in numerous application scenarios. A cascade of so-called Cycle-consistent Generative Adversarial Networks (CycleGANs) is used to convert neutral voice into emotional voice. This type of deep neural networks is explained in more detail in Section 4.4.2.2.

4.4.2 Emotional voice conversion with CycleGANs

For the transformation from neutral speech to emotional speech we decided to use methods of adversarial learning, as existing research showed great potential of these types of algorithms in related fields (Fang et al., 2018; Kameoka et al., 2018). In the following sections, the basic concepts behind this group of methods are explained.

4.4.2.1 Generative Adversarial Networks

In 2014, Ian Goodfellow et al. presented the first version of GANs (Goodfellow et al., 2014). His work, as well as most of the concepts based on it (see for example (Denton et al., 2015; Radford et al., 2015; Mao et al., 2017)), used GANs in the field of image processing. Since then, multiple modifications were made to the original architecture to also address tasks that are related to audio processing.
GANs are composed of two different neural networks, the so-called generator and the discriminator (Goodfellow et al., 2014).
The task of the generator network is to generate new artificial data x from stochastic noise vectors z, that are often referred to as the Latent Space (see (Wu et al., 2016; Wan et al., 2017)). The discriminator distinguishes artificial data from real data (Goodfellow et al., 2014). The two networks are combined by adding the output of the generator and real data as training data to the discriminator. The respective objectives of the two networks can be interpreted as follows:
The generator tries to fool the discriminator with fake data while the discriminator tries to expose the generator. The two networks can therefore be seen as competitive opponents which gives rise to the term *adversarial*.
The figure below illustrates this scheme. By the fact that the whole combination of generator and discriminator is only fed with the original raw training data of the problem domain, but not with any label information, GANs are assigned to the group of *Unsupervised Learning* methods.

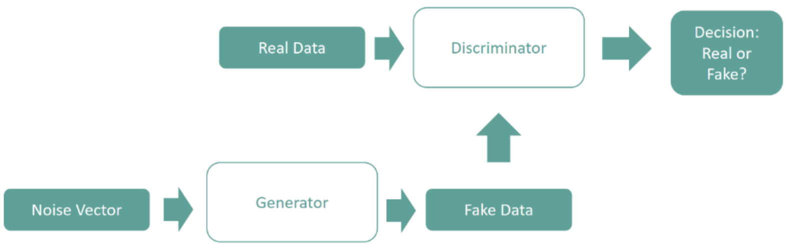


Figure 7: Basic GAN Architecture

The following paragraphs give a more detailed and mathematical view of both the discriminator and generator network.

- **Discriminator Network:** The discriminator is, as already described, necessary to distinguish real training data from artificially generated data.
  The distinction between the data represents a binary classification problem. A typical discriminator network is therefore designed as a network with a single output node. The hidden layers, that is, the node layers between the input and output layers, in

state-of-the-art architectures are formed by convolution layers, which during the training process, learn to apply any filters to the input data. Thus, the discriminator is an instance of the class of Convolutional Neural Networks (CNNs).
CNNs are deep neural networks that contain layers that represent image processing filters. During the training process, CNNs are learning how to adjust the weights of these filters so that the function that shall be learned by the network can be approximated. For more detailed information on CNNs, reference is made to Aghdam and Heravi (Aghdam and Heravi, 2017). The loss function required for training is defined with the help of a so-called crossentropy. The loss function represents the error which the network produces with each training sample. The crossentropy is defined as *p * log(q).*
The variable *p* represents the actual class of the input, also referred to as *Ground Truth*, while *q* is the value that was approximated by the network. This allows the formulation of an elegant loss function for the discriminator:

$$\max_{D} V(D) = \mathbb{E}_{x \sim p_{data}(x)}[logD(x)] + \mathbb{E}_{z \sim p_z(z)}[log(1 - D(G(z)))]$$

- **Generator Network:** The generation of the new data is carried out by the generator. The generator learns to generate outputs whose distribution is similar to that of the training data. For example, if you look at audio recordings of a certain corpus, they usually have a similar structure with regard to different properties like frequency combinations and temporal structure. However, the structures differ from one another which corresponds to a certain distribution. The generator shall learn how to adapt this distribution, i.e. it should generate different output data for different inputs, where the outputs have the same distribution as those of the training corpus. The ground truth is generated by the discriminator, which is passed as implicit label to the output layer of the generator during training. Thus, the loss function for the generator would be:

$$\min_{G} V(G) = \mathbb{E}_{z \sim p_z(z)}[log(1 - D(G(z)))]$$

- **Combination of both networks:** Now that the objective functions of the two individual components of the network are known, single objective function of a GAN can be aggregated:

$$\min_{G} \max_{D} V(D, G) = \mathbb{E}_{x \sim p_{data}(x)}[logD(x)] + \mathbb{E}_{z \sim p_z(z)}[log(1 - D(G(z)))]$$

Since this equation requires minimization by the generator and maximization by the discriminator, the concept of GANs is also referred to as *Minmax Game* (Goodfellow et al., 2014). During the training process, discriminator and generator are trained alternately using the relevant parts of the objective function respectively.

4.4.2.2 CycleGAN Architecture

The original GANs introduced in the previous paragraph are capable of generating new realistic data from random noise. However, in order to achieve voice conversion, existing data must be modified instead of taking noise vectors as input. To achieve this goal, the system developed for PRESENT makes use of a CycleGAN architecture. CycleGANs were introduced by Zhu et al. (Zhu et al., 2017) and combine two single GANs to perform a style conversion of existing data instead of generating completely new data.

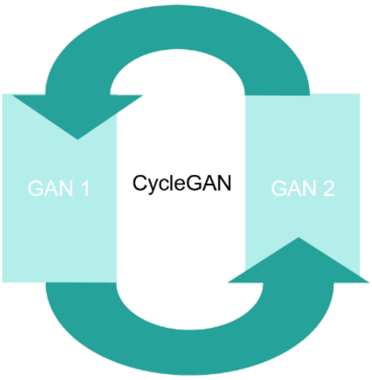
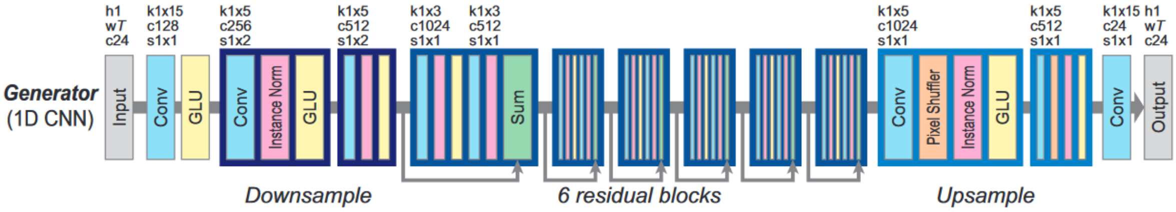


Figure 8: CycleGAN components

The two individual GAN networks are interconnected in such a way that the output of one network serves as input for the other network and vice versa. The discriminators of the networks are each trained on different data partitions, which correspond to different domains. In the context of Emotional Style Conversion such a domain corresponds to a single emotion. By receiving the output of the other GAN as input, the generators learn to transform the corresponding audio data between the domains. Additionally to the loss components that were explained in the previous section and make sure that the newly generated data appears realistic, a further component is included to the loss function of the CycleGAN.
This additional part, the so-called *Cycle-Consistency-Loss*, measures the similarity between two audio samples when the first one is fed into the first GAN, and the output of that GAN is fed back into the second GAN. Thus, the audio sample is first transferred into another emotion, before it then is transferred back into the original emotion. Keeping that loss small ensures that the CycleGAN learns only to alter emotion-relevant features and to keep other features the same. This way, speaker identity and speech information remains the same.

For our experiments, we made use of a CycleGAN architecture that was initially developed for speaker-conversion, i.e. for transferring utterances of one speaker to the same utterances spoken by another speaker. The used architecture is depicted in Figure 9.



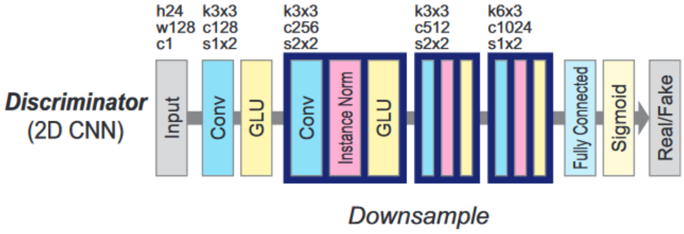


Figure 9: CycleGAN architecture: Generator, Discriminator (Kaneko and Kameoka, 2017)

As stated above, the goal of our system is to convert speech data of neutral emotion that is produced by a TTS system to speech data of emotional voice. As neural networks need a certain amount of training data, we had to introduce a further intermediate step. As we want to force the CycleGAN to only convert emotional characteristics, we needed training data of one single speaker in neutral emotion and other emotions, so that the network does not have to convert the speaker identity. We did experiments with converting speaker identity and emotional information in one single step, but we found out that the CycleGAN that we used doesn't have the capabilities to achieve sufficient results. Thus, we decided to use a cascade of two CycleGANs: The first one has the task to transform neutral voice of the TTS voice to neutral voice of a speaker that we have an emotional dataset for. The second CycleGAN learns to convert the neutral voice of that speaker to the respective emotions. This way, one CycleGAN only has to learn a speaker conversion, and the other one only has to perform an emotional voice conversion. This ensures that the training task for each of the networks is not too hard to learn. By building that cascade, we can achieve a voice conversion of a neutral TTS voice to an emotional voice of a speaker that we have data for. The process is depicted in the figure below.

4.4.2.3 Dataset

It is planned to train the CycleGANs on a dataset that contains different emotions of the actor that is also used for the visual character models of PRESENT. However, for our experiments so far we used an already existing dataset, namely the *Emotional Voices Database*, that was introduced by Adigwe et al. (Adigwe et al., 2018). We trained the network on the classes *neutral, amused* and *angry*. In the next steps, it is planned to extend the emotions to the ones that we also used for the calculation of the inner emotional state of the agent. Once this step is done, a field-study for evaluation purposes can be done.

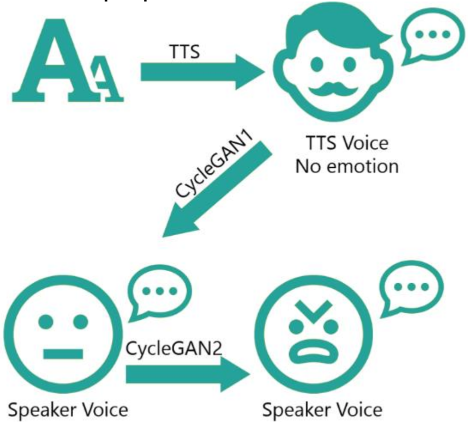


Figure 10: Emotional style conversion using CycleGANs

5 Future plans

In this section we outline a road map for our plans in the future. Therefore, we plan to enhance the PRESENT project in the following areas: Behaviour adaption, its combination with humour and the speaking style of the agent.

Concerning the behaviour adaption we plan to equip the agent with different reward signals. The agent is rewarded with measurements about interaction quality. In this context we plan to integrate social signals of the user provided by WP4 Task 3 (valence and arousal). These implicit user reactions provide us with feedback needed for the described Socially-Aware reinforcement learning process which is used to adapt the agent behaviour to the user preferences. As a first approach for behaviour adaption we will implement an agent showing different levels of extraversion. Varying degrees of extraversion can be shown by e.g. low voice volume (low extraversion) or room-filling postures (high extraversion).
In addition to the adaption of nonverbal behaviour we are planning to give the agent the ability to apply humour, again tailored towards the user preferences. There are two main types of humour: canned and conversational humour. The first one equal mostly simple cohered jokes, the latter one refers to the conversation context. Since we presume a covariance between the preferred agent behaviour and the application of a specific type of humour, it is planned to investigate the combination of agent behaviour with the applied form of humour.
Concerning the voice adaption we also plan to give the agent different speaking styles. This can for example include different dialects, female or male voices and specific accents.

Developments in these areas provide the agent with the ability to show various combinations of behavioural traits. This addresses the diversity of the agent and aims to enable an diversified communication.

6 Conclusion

In this document, we first set an theoretical understanding on how personality and interpersonal communication works. Addressing the first task of our work package (WP4T1: Enhancement of non-verbal agent behaviour) we defined different behavioural traits, which according to the psychological theories from the literature aim to enhance the interaction quality between the agent and the user.

The first main behavioural tweak concerns the calculation of an internal emotional state, which will help in assembling emotional behaviour and enables the agent to show empathy. In this context a new calculation method for the internal emotional state was conceptually designed, which will be implemented in one of our next steps.
Addressing the first and the second task of our work package (WP4T1: Enhancement of non-verbal agent behaviour, WP4T2: User focused agent adaption via context consideration, reinforcement learning and social signal feedback), the second main adjustment in behavioural traits is related to personality adaption according to individual user preferences. Therefore, as a first step we developed a reinforcement learning system encompassing a K-Armed Bandit and Q-Learning algorithm. To realize the personality adaption we additionally reviewed the literature and found verbal, nonverbal and paralinguistic cues for the expression of extraversion. In order to make our reinforcement learning process Socially-Aware and to test the basic functionality of the our reinforcement learning framework and the personality adaption, we defined ideas for a corresponding demonstrator application.
The third main tuning step for the agent's behaviour pertains to the voice adaption. This includes the generation and conversion of an emotional voice from a mere text input.

Furthermore after talking about the completed tasks of every main trait adaption mechanism the next steps to be taken in this project were discussed (see sections 4.2.3, 4.3.2.7 and 5). The first two defined behavioural traits depend on the emotion recognition outputs from

Deliverable 4.2. Since this social signals provide a crucial input for the adaption components, one of the next steps will be to integrate the recognition pipeline of Deliverable 4.2. The dependence on the user behaviour determines the expected behaviour of the agent according to the emotion state calculation or the Socially-Aware Reinforcement Learning Task. The first one will synthesize an empathetic behaviour with respect to show the corresponding emotions, the latter one will adapt the degree of extraversion and the body modalities used to express the learned degree of extraversion.

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