Rapport - Establishing Harmonious Relationship Between Robots and Humans

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Abstract Autonomous agents are becoming our next companions. They may be able to offer physical therapy assistance, play games and even help us treat weight loss. However, it is not enough to build agents that are socially engaging and attractive at first, they need to continuously convey such feelings and encourage user interactions, i.e., to build and maintain rapport over long periods of time. In this work, we propose a novel approach for learning subconscious behaviours from humans based on limited-perception Wizard-of-Oz with human experts to provide corrective feedback in order to create a generic "rapport" model for an autonomous agent. The proposed method will be incorporated, trained, and tested on a robotic rapport agent, EMYS, set up in a negotiation scenario, the Split Or Steal game. Following current literature on rapport and HRI, we propose a hybrid architecture that combines both rule-based and Machine Learning based components. On the first component we model high-level behavioural rules that are easier to specify, and on the second component, we use Reinforcement Learning techniques to generate correct backchannels (listener behaviours) that would be harder to specify otherwise. Lastly, we will evaluate the effectiveness of the proposed approach on learning subconscious behaviour, the quality of the rapport agent, and the impact of rapport on cooperation in the negotiation scenario.

Keywords: Rapport, Backchannel, Reinforcement Learning, Machine Learning, Human-Robot Interaction, SERA, Wizard-of-Oz, EMYS

Contents

1 Introduction

Robots are increasingly becoming part of our society and their presence has been proven to impact our lives. But do any of us remember a remarkable interaction with a robot to the same degree we are able to recall one with a person? What makes one conversation memorable? People can do this so easily and establish rapport rapidly. How can we design robots that can achieve something that has so much impact?

In order to answer these questions, the Human-Robot Interaction (HRI) research community has been exploring agents capable of responding emotionally and more humanly in dyadic interactions. More specifically, researchers have been exploring how to exhibit signs of friendliness, coordination, and attentiveness in dyadic interactions. In other words, researchers have been studying how to develop rapport agents. These agents are being applied in several domains such as education [1], autism [2,3], child care [4], medical assistances [5,6], family companions [7], weight loss [8], and several other examples [9,10].

In order to improve the agents' performance, several studies were conducted to identify how to influence people using different verbal and non-verbal strategies. There is evidence in these studies that rapport agents can make people feel: more connected [11,12], less tense [13], less embarrassed [14], and more capable of trusting [14]. However, the impact depends on how such strategies are executed. For example, a poorly timed head nod, a backchannel to generate coordination and attentiveness, may reduce rapport.

Despite present efforts regarding rapport, there are still important issues that can be further improved and the proposal intends to address, namely:

(i) Lack of studies on how backchannels Machine Learning (ML) based prediction models benefit from Wizard-of-Oz (WoZ) studies;
(ii) Methods to train virtual agents to simulate subconscious human behaviour;
(iii) Lack of robotic rapport agents that is capable of eliciting every component of rapport: positivity, coordination and mutual attention.

We propose extending the Socially Expressive Robotics Architecture (SERA) [15] framework to manage rapport in dyadic settings because it is integrated into several robotic agents, and because it is being developed internally in Intelligent Agents and Synthetic Characters Group (GAIPS). The proposed solution will use a hybrid architecture with one rule-based component to model high-level interactional rules that are easy to specify, and two ML based components to model appropriate timings and actions for backchannels, respectively. Following current literature, we will use Reinforcement Learning (RL) [16–22] (Section 2.3).

The ML-based components will be trained using a novel approach to learn subconscious human behaviours based on a modified limited perception WoZ [23, 24] with human experts providing corrective feedback.

To evaluate the proposed solution, a rapport agent will be developed, trained and tested on a dyadic negotiation game setting based on the Split Or Steal game using robot EMotive headY System (EMYS). We expect the developed system to stimulate the essential components of rapport: positivity through the rule-based component, and attentiveness and coordination through the previous learnt ML models. The evaluation will measure the effectiveness of the proposed approach on learning subconscious behaviour, the quality of the rapport agent, and the impact of rapport on cooperation in the proposed negotiation scenario.

1.1 Objectives and Expected Contributions

The main goal is to improve current predictive models for backchannels (which are essential to build rapport agents) to be used on robots with inherent limitations over the environment, regarding its perceptions and actions. To solve this issue, we propose to:

(i) Extend the SERA framework to support rapport management using a hybrid controller with a rule-based component, and two ML-based components trained with the proposed approach;
(ii) Create a rule-based component for managing rapport which will be the baseline for training and evaluation;
(iii) Train a ML classifier to assess socially adequate timings for backchannel generation;
(iv) Train a ML classifier to determine the most appropriate backchannel during interactions;
(v) Integrate the rapport agent on a negotiation scenario, Split Or Steal game;
(vi) Conduct a study to compare the final rapport agent with the baseline.

Lastly, the expected contributions of this proposal are:

(i) A novel approach to learn subconscious information from human subjects based on a limited-perception WoZ [23];
(ii) Studies over the impact of our proposed approach over training backchannels predictive models;
(iii) Improvement over previous rapport agents regarding their quality and naturalness;
(iv) Extension of SERA framework to support rapport management in dyadic interactions.

The remainder of the document is organised as follows. Section 2 describes rapport, Machine Learning, and Reinforcement Learning. Section 3 describes the current state-of-art in rapport agents. Sections 4 and 5, describe, respectively, the proposed solution and the implementation and methodology for evaluation. Lastly, the conclusions and the planning will be addressed in Section 6.

2 Background

For the following sections, the main concepts of the document will be described. Section 2.1 describes the concept of rapport since it is the main phenomenon we want to elicit on people's perception. Currently, researchers have been starting to use Machine Learning approaches which Section 2.1 describes. Lastly, Section 2.3 describes Reinforcement Learning ML techniques, following current suggestions made by several researchers [16–19, 23].

2.1 Rapport

The feeling of flow and connection during interactions is formally known as rapport [25]. It is a phenomenon that affects people on three levels: emotional, behavioural and cognitive [25].

The emotional level refers to the impact the relationship has on partners, while behavioural refers to, for example, the convergence of movements and facial expressions. Finally, the cognitive level refers to a shared understanding between conversational partners [25].

Spender Oatey [26] suggests that rapport management can be divided into three main tasks: enhancement, maintaining and destroy. The first task aims to create strong first impressions, the second encourages the continuation and the third task aims to destroy relationships. Each one of these tasks can be modelled as abstract goals that can be accomplished by achieving sub-goals only satisfied by interacting with the external world [18, 19] (see Figure 1). These sub-goals manipulate the three components of rapport suggested by Tickle-Degnen and Rosenthal [27]:

- **Positivity**: feeling of approval and friendliness (e.g. head nod and smile);
- **Mutual attention**: feeling that the other's attention is focused on the individual (e.g. mutual gaze and "hmm hmm" vocalisations);
- **Coordination**: feeling of predictability and being in-sync (e.g. postural mimicry and synchronised movements).

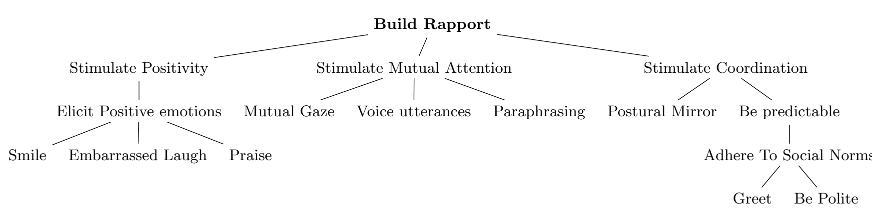

Figure 1: Example plan for building rapport. The nodes are goals and the leafs are actions.

However, in order to build rapport, it is essential that these three components co-exist during an interaction [13, 18, 28, 29]. For example, using gaze to establish mutual attention conveys disinterest and can have negative social effect if not accompanied by other behaviours that stimulate positivity and coordination [13]. Although, the relative weights of these components may change as the relationship evolves beyond strangers [13, 18, 29].

Moreover, two strangers behaviours are initially driven by cultural conventions as they do not know each other and, therefore, they expect what was taught by their cultural environment according to the current context [18] (e.g. greet and be polite). As the relationship evolves and the interlocutors get to know one another, positivity decreases and it is replaced by coordination while mutual attention remains constant [18, 27]. The interlocutors may even violate what is culturally accepted in order to meet interactional goals and behavioural expectations [18]. For example, friends may use sarcasm and insults instead of politeness [18]. Table 1 describes examples of verbal and non-verbal strategies for managing rapport.

Verbal	Humour; Paraphrasing; Self disclosure; Praise; Ego Suspension. Refer to shared experience; Slower rate of speech; Small-talk;
Non-verbal	Gaze; Smile; Reciprocate previous action. Silence; Postural mimicry; Gesture mimicry; Mirror Facial Expression; Head gestures.

Table 1: Examples of strategies and actions to manage rapport.

Learning behavioural expectation is also important to assess rapport success. This can be achieved through the use of self-disclosure [30], small-talk [31] and humour [32]. For instance, when self-disclosure is successful, it is reciprocal, intimacy increases, disclosed topics become more diversified, and deeper [18]. Moreover, assessing when rapport strategies were successful is also important, for example, mutual gaze and smiling become more noticeable and consistent [18,28].

To sum up, rapport is a phenomenon that makes interactions more engaging and harmonious. Rapport management can be modelled as a problem of goal satisfaction that is solved through the realisation of actions. However, the strategies for managing rapport must take into account the goals of the interaction and the sociocultural context of the interaction in order to satisfy behavioural expectations. Although, these expectations may not be clear at first and strategies for learning them should be applied.

2.2 Machine Learning

Machine Learning (ML) is a subfield in Computer Science that develops algorithms capable of automatically learn and make predictions based on data [33]. In supervised learning, the data is retrieved from datasets or corpus, and in unsupervised learning, the data is directly sampled from the interaction. Despite not requiring handcrafted rules, these algorithms requires large amounts of quality data and good discriminative features in order to create good predicting models or classifiers. However, acquiring great amount of data may prove difficult in HRI since it takes a great toll on the development design as it requires careful preparation, feature selection, data processing techniques, and most of all, test subjects (Figure 2).

In addition, preliminary studies, in the intended scenario, are crucial to assess the most relevant interactions, and behavioural features we have to look before starting the training stage (see relation between the dataset and training in Figure 2). One must take into account that excessive features may lead to redundancy (noise) contributing negatively to the quality of the classifier (overfitting). Therefore, it is recommended to use less features in order to have better generic model.

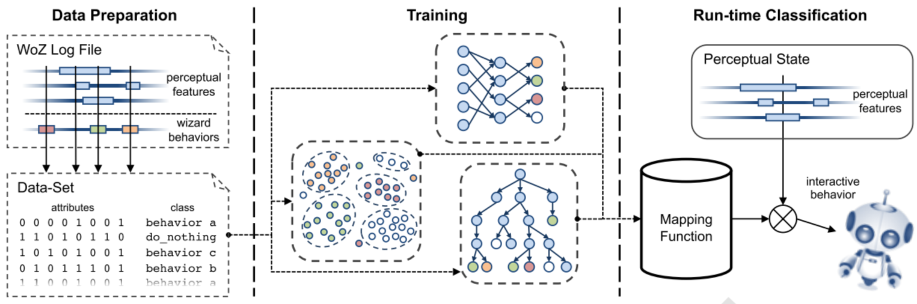

Figure 2: Illustration of a ML system in a HRI application. The dataset is collected and prepared, then it is given to a ML algorithm, and lastly, in run-time, the mapping function returns the most appropriate response given an input. From [23].

Finally, the predictive models' performance are tested using data that were not used during the training stage (test set and training set respectively). In order to limit overfitting issues, model validation techniques such as cross validation are used to test if the classifier is sufficiently generic to any given independent test dataset.

Usually, in supervised learning, the performance is measured regarding the precision (Equation 1) and recall (Equation 2) of the generated output according to the what is expected in the corpus (TP, FP, and FN stands for True Positives, False Positives, and False Negatives, respectively).

$$Precision = \frac{TP}{TP + FP} \quad (1) \qquad\qquad Recall = \frac{TP}{TP + FN} \quad (2)$$

2.3 Reinforcement Learning

Reinforcement Learning (RL) is sub-field in ML that guides agents' actions, in an environment, to maximise a cumulative reward [34,35]. RL systems contain:

- A set of possible world states S;
- A set of possible actions A;
- Transitioning rules between states;
- A immediate reward function $R(s, s', a)$ with $a \in A$, and $s, s' \in S$;
- Rules to describe the environment.

Typically, these systems deal with environments where the optimal reward function might not be clear [34]. To tackle this issue, RL agents uses exploration strategies to find the best policy function $\pi(s)$ that returns the most probable action $a \in A$, given a state $s \in S$, that maximises the cumulative reward (Equation 3). In social behaviours, agents that are eager to interact with its partner (instead of being silent) will acquire more information regarding it's performance during interactions and will be able to learn more quickly as they test new different interactional strategies.

$$\pi(s) = a,\, a \in A \, and \, s \in S \tag{3}$$

One well researched RL algorithm is Q-Learning [35]. In Q-Learning, the virtual agents learns and stores Q-Values that depends on the reward value for a given action $R(s_t, a_t, s_{t+1})$, on an estimation of future reward $\max_a Q(s_{t+1}, a)$, on the learning rate $\alpha_t \in [0, 1]$, and on the discount value $\gamma \in [0, 1]$ (Equation 4). The learning rate α_t defines the weight of old information during learning, and the discount value γ defines the weight of future rewards.

$$Q(s_t, a_t) = (1 - \alpha_t)Q(s_t, a_t) + \alpha_t \left[R(s_t, a_t, s_{t+1}) + \gamma \max_a Q(s_{t+1}, a) \right] \tag{4}$$

The Q-Values can be zero at the beginning of the learning process, meaning that the agent's does not have previous, or, value different than zero, meaning the the agent has previous knowledge [36]. The values for α and γ are defined according to the developed scenario, the purposes of the agents and overall quality of the final RL model.

Lastly, there are two main issues when using RL: identifying the reward function and gathering data to satisfy the combinatorial explosion of environment features and possible actions. To solve the first issue, authors suggest extracting the reward function from human experts during demonstrations using inverse RL [16, 37]. That is, collect feedback from human experts regarding the virtual agent's performance and use the information collected to define a reward function. To solve the second issue, the model should take into account fewer environment features and actions.

3 Related Work

Several virtual agents have been developed to study the impact of specific rapport strategies on the user perception of naturalness and social behaviour adequacy. The following sections describe the state-of-art in rapport and agents that are capable, at some extent, of managing rapport.

Section 3.1 describes current theoretical models for building rapport agents. Sections 3.2, 3.3 describe virtual agents based on rules and ML classifiers, respectively. Section 3.4 briefly describes current methodologies to learn social behaviours from WoZ studies.

Lastly, Section 3.5 discusses the current state-of-art and makes a brief comparison between the most important systems and their relevance and contribution to the proposed solution.

3.1 Theoretical Models of Rapport for Agents

Rapport is a mostly unconscious phenomenon [38] that occurs during interactions marked by strong perceptions of coordination, positivity and mutual attention.

The most important concepts for managing rapport are: planning social behaviours (Figure 1), learning social behaviours and flexible mechanisms to regulate current actions. Rapport models involve several complex cognitive mechanisms. Therefore it is beneficial to discretise it into smaller sets capable of, for example, enhancing positivity (friendliness) using self-disclosure or enhancing coordination and attentiveness through backchannel and turn-taking strategies [39–41]. The latter strategies are allied with good listeners as they must able to understand how to provide well-timed adequate feedback (backchannel) and identify appropriate moments to become the speaker (turn taking) and incite further dialogue [39, 42].

Zhao, Papangelis, and Cassell, propose a theoretical model to manage long-term rapport [18, 19] that is very relevant for current implementations of long-term social companionship agents [5–7]. Similarly to what was described previously in Section 2.1, the proposed model treats rapport as an interactional goal that is satisfied through strategies and actions according to the current state of the interaction and the user model (See Table 2).

The strategies and the selected actions, despite initially representing the general sociocultural norms, must adapt to the interpersonal norms of the relationship and the context [18]. As the relationship evolves, the dyadic state and the internal models should be updated in order to store the most accurate description of the interaction and return better behavioural responses that satisfy the dyad behavioural expectations [19].

Dyadic State	Rapport State; Behavioural model; Friendship Status; History
User Model	User goals; Shared knowledge; Task model; Conversational Agent putative dyadic state

Table 2: Relevant data structures for rapport models. Adapted from [18].

Another important aspect for managing rapport is the ability to continuously adapt to the current interaction and context, give incremental feedback [38, 43–45], and even recover from mistakes [40]. Its usefulness is remarked on complex synchronised behaviours such as speech and handshakes [38]. This requires bidirectional connections between the behaviour realisers and the behaviour planners to enable quicker corrections [44]. This also requires incremental planning and execution of behavioural chunks that can be potentially interrupted, modified or even replaced [38, 43–45]. This approach moves away from the typical SAIBA model [46] and requires extending the current Behaviour Markup Language (BML) [38, 43, 44] specifications.

3.2 Creating Rapport Agents using Rule-Based Approaches

In the context of the document, we consider rule-based systems as systems that use rules implicitly or explicitly. For example, the former mimics head gestures using motion sensors and the latter generates backchannel behaviours if the conversational partner pauses his speech for more than one second. Rule-based systems are great for deterministic scenarios where the agent does not need to be as robust as other systems used in non-deterministic scenarios [22] where rules might not be easy to define. However, these systems are not easily ported to other scenarios, nor are they easily scalable because they are often based on non-trivial conditions [17], and are often specifically tailored to discrete scenarios.

Mutlu et al., implemented a scripted mutual gaze agent that synchronises gaze behaviour with pre-recorded voice and gestures [22]. In their experience, they concluded that participants would recall the story better when the robot looked at them more. Additionally, using the same gaze frequency, women felt better when the storytelling agent gazed less at them. This is important if we want to develop agents for education scenarios where transmitting information is crucial.

Stanton et al., developed a robot assistant for a cooperative visual tracking game (the "shell game") [47]. Volunteers would ask the robot for help. However, occasionally, the robot would volunteer to give an answer. In their experiment, they concluded that eye gaze can have powerful effects upon participant decision-making and behaviour, and influence their task performance. For example, humans tend to comply to the robot's suggestion when it gazed at them on harder tasks but, on easier tasks, gaze reduced trust. The authors postulates that "robot gaze can have either a positive or negative impact upon trust and compliance, depending upon the nature of the robot's request or suggestion".

Andrist et al., developed a virtual agent focused on mutual-gaze behaviour in a therapy scenario [21] that would systematically swap its gazing target between the task area and the conversational partner's using tracking sensors. According to their study, matching gaze behaviour models to the user's personality increases motivation and engagement in repetitive tasks. In other words, different personalities require different rules. For example, between tasks, when therapists would provide encouragement, introverts shift more often their gaze to the therapist than extroverts.

3.3 Creating Rapport Agent using Data-Driven Based Approaches

Rule-based systems are not easily scalable seeing that it is impossible to program an agent to handle every possible situation and outcome, especially when interacting with the unpredictability of human behaviour. Therefore, some scenarios may benefit of having agents capable of adapting to changes in the external world and act accordingly using data-driven models. We consider data-driven systems, or ML-based systems, as systems that use data collected from studies to train ML classifiers and generate appropriate social behaviours.

Mohammad et al., propose a model for interactive robots that can learn how to interact naturally with human conversational partners in different environments and contexts [48] using unsupervised learning. One of the tested successful scenarios was learning how to apply backchannels in a dyadic setting with a human instructor. According to their results, as expected, the system performs better than the traditional rule-based, however, there is no comparison regarding the traditional supervised learning approaches.

Cakmak, Thomaz and colleagues have been researching the potential of active learning on agents that actively seek information and fill gaps in their knowledge, potentially improving their performance [16,49–51]. In their studies, they noticed that people who better understand the agent's queries are able to train the model with "perfect accuracy relatively quickly" and had more confidence on the trained model performance [49]. However, previous work has been more focused on learning task related information and not, as intended in the present document, learning better interactional models to build and maintain rapport.

Current literature on rapport and virtual agents, uses Conditional Random Field (CRF) [52], Suport Vector Machine (SVM) [17], and RL [16] as classifiers. However every author suggests exploring RL algorithms, such as Q-learning (detailed in Section 2.3) to learn human social behaviours [16–21].

Moreover, it is important to properly design the experiments to correctly collect data. For example, Thomaz et al., developed an agent using RL learning [16]. During the experiment, despite asking the humans not to provide feedback (only guidance), they influenced the results. As the author describes "people use the reward signal to give anticipatory rewards, or future directed guidance for the agent".

3.3.1 Virtual Rapport 2.0

Huang et al., developed a short-term rapport agent to enhance mutual attention and coordination using backchannels through a data-driven approach that takes into account context-specific response models in a dyadic conversational setting [52]. The model determines the best suitable timings to generate specific backchannel behaviours and turn-taking opportunities according to the perceptual state observed.

System description Following Figure 3, the system contains the following modules:

- ***Perception***: analyses human speaker's behaviour in real time;
- ***Response Models***: predicts timing of backchannel feedback and end-of-turn opportunities in real time using information from the environment and from the agent itself. It also decides which behaviour to generate;
- ***Generation***: generates the output from the response models;
- ***Consensus Data***: contains data collected from Rapport 06-07 dataset and Self-disclosure data-set (`http://rapport.ict.usc.edu`) using Parasocial Consensus Sampling (PCS). The data contains dyadic interactions between a human speaker telling a story and human silent listener.

As depicted in Figure 3 there are three models in the *Response Models* module: *End-of-turn*, *Backchannel*, and *Affective*.

The first model, *end-of-turn*, using a rule-based approach, identifies turn-taking opportunities by analysing the current speaker's non-verbal behaviours.

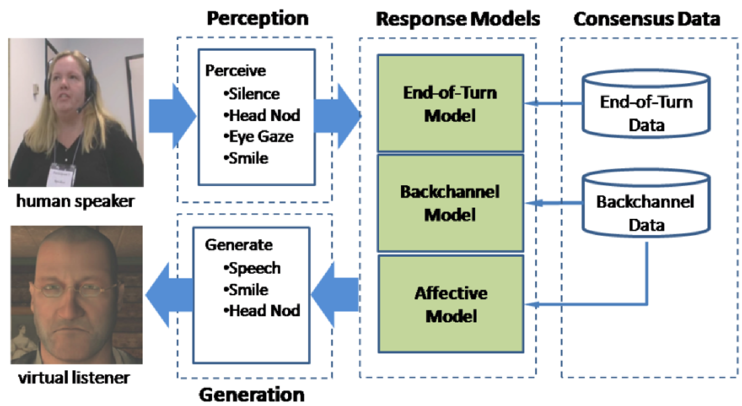

Figure 3: Architecture of Virtual Rapport 2.0: The *Perception* module analyses human behaviour in real time. PCS data is used to create the *Response Models* module. Lastly, the output of the models is generated by the *Generation* module. From [52].

For example, if the human interrupts the virtual agent, the agent stops, yields his turn and, says “I am sorry, keep going” while showing a facial expression [52].

The second model, *Backchannel*, is ML-based (using forward-only inference CRF for real-time predictions) and trained using the Rapport 06-07 dataset. It is capable of predicting when and how to give non-verbal feedback.

The last model, *Affective*, analyses facial feature points in real time and detects whenever the speaker is smiling.

During the interaction, the three response models are used in conjunction to decide whenever it is appropriate to generate a backchannel. If the speaker is smiling (according to the *Affective* model) and if it is a good opportunity to generate a backchannel (according to the *Backchannel* model) then a head nod (one of the three identified in their studies) is generated accompanied by a smile.

Evaluation The developed virtual agent interacted with the human subjects in a interview environments in which the former was the interviewer and the later the interviewed. With the goal of comparing the developed system with the previous version [53], the evaluation measured the following dimensions: rapport (five-item social presence scale [54]), overall naturalness, backchannel feedback and end-of-turn prediction.

Discussion The results demonstrates a significant improvement over the previous version. Over 90% of the users preferred the Virtual Rapport 2.0 rapport agent over the previous rule-based system [53,55]. The timing’s precision and recall are much better, leading to a better synchronism and perceived naturalness from the user during the interaction. According to the authors, the data-driven design, the much richer set of emotions capable of mimicking smiles, and the generation of more natural head gestures might explain the overall better results on the stronger feelings of rapport.

To conclude the most relevant aspects of the system are:

– Corpus based approach;
– Identification of different head nods patterns;
– Duality of ML-bases decision and smile to generate backchannel behaviour;
– Creative strategy for handling interruptions.

3.3.2 Iterative Perceptual Learning

Kok et al., developed an iterative data-driven rapport model focused on generating timings for backchannel behaviours in a dyadic conversational setting [17]. The learning stage is iterated several times, each one is more refined and capable of representing generalised behaviours than the previous one.

Usually, corpus-based backchannel models retrieves negative samples from random moments in the interaction that do not overlap with the positive samples marked in the corpus [17]. However, this approach potentially leads to greater number of false negatives by not taking into account that social signals are optional and a reflection of the listener's personality. Therefore different behaviour from the corpus can also be recognised as socially appropriate. In order to tackle this issue, Iterative Perceptual Learning (IPL), generates social signals and uses perceptual (subjective) evaluation to identify the moments in the interaction that are perceived as socially appropriate and inappropriate.

System Description Following the representation of the IPL system in Figure 4, the system starts with an initial ML model (yellow area) that is trained using the corpus-based mentioned. From the corpus [56] it was extracted three types of features: prosody (112 features), speaking (1 feature) and looking (1 feature). After the first subjective evaluation, the negative samples are discarded and replaced by the ones rated by the users. Then, through several iterations of generation (pink areas), evaluation (blue areas), and learning (green areas) the model is refined and its understanding regarding proper timings for social behaviour evolves.

During the generation, non-verbal behaviours are computer generated according to the ML classifier and the feature vectors created from the partner's behaviour at a given instance. Then, during the evaluation, using PCS [57], multiple subjects evaluate the generated behaviours by pressing a *Yuck* button whenever they would rate the agent's behaviour as socially inappropriate [58]. Finally, during the final stage (learning) the retrieved positive and negatives samples are used to train the classifier.

Evaluation In the evaluation, in each iteration, the authors compared the traditional corpus-based with the iterative approach on face-to-face conversations between the IPL agent (listener) and a human subject (speaker) using precision (Equation 1), recall (Equation 2), and perceptual evaluation (*Yuck* button). The experiment lasted for 4 iterations, and the corpus-based system and IPL system were trained using the same interactions. The stimuli was a speaker's video from

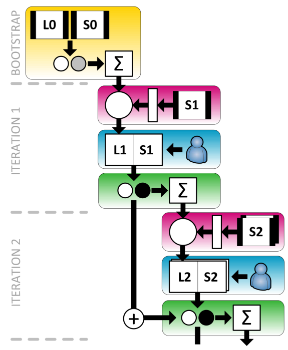

Figure 4: Schematic representation of the IPL framework. The generation, evaluation and learning stage are shown in pink, blue and green, respectively. From [17].

the corpus with a synchronised animated listener capable of only nodding his head while making utterances.

Discussion Human subjects perceived the IPL virtual agent's backchannels as natural. However, the system was limited because it lacked other relevant features to manage rapport, e.g., mutual gaze, smile, and head angles. This led to, as the author describes, "a rapid saturation of the model". Additionally, the authors recommend avoiding SVM models because they are not sequential (do not analyse sequential patterns).

To conclude there are several relevant positive aspects from the model to the proposed solution:

- Iterative approach that is continuously refined and improved;
- Perceptual evaluation to identify inappropriate moments in the interactions;
- Limiting the listener's perception and increase his focus by limiting the agent's actions;
- Generate 25% more backchannels for the training stage in order to collect more data.

3.3.3 Sensitive Artificial Listeners

Schröder et al. developed a virtual agent integrated in SEMAINE [59] called Sensitive Artificial Listeners (SAL) that has the required capabilities to sustain conversational dialogues and be a good listener [60].

System Description Following the representation of the SAL system in Figure 5, the most relevant components are: *Feature extractors*, *Analysers*, *Interpreters*, *Action proposers*, and *Action selection*. The *Feature extractors* component extracts several features such as head gestures, facial features, emotions and, most of all, acoustic features. These features are later analysed by the *Analysers* and *Interpreters* components. The former component analyses non-verbal behaviours and speaker's emotions to produce an estimate of the information's reliability. The later component, given the information available, returns the best state representation for the user, dialogue and agent. Following this, several *Action proposers* will propose an action, in parallel, given previous information. Following, the *Action selection* component selects the action with the highest estimated quality, and lastly, the *Behaviour generator* generates the desired action (utterances and facial animations).

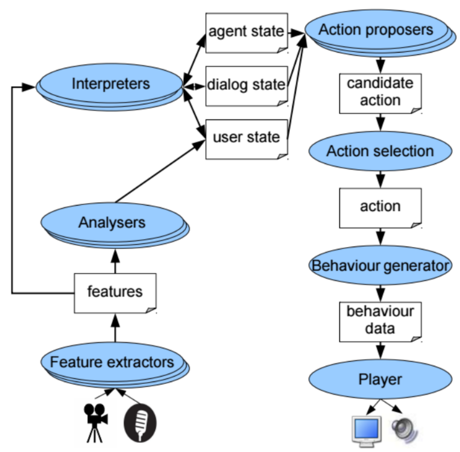

Figure 5: Sensitive Artificial Listeners conceptual architecture. From [60].

The agent is capable of identifying whether it should be in listener or in speaker mode. This is relevant as the *Action selection* component gives more priority over speaker's actions. An example speaker action would be saying "Well?" or "Go on, tell me your news!" after a long pause. In addition, in listener mode, the *Action selection* component chooses the most appropriate backchannel to be produced according to the emotions and interest level estimated from the user.

Evaluation The objective was to evaluate if emotion-related abilities influence the quality of human interactions. Firstly the users, with minimal HRI experience, receive a introductory briefing on the available personalities they can interact with (4 in total). Then, they can interact twice with each available personality one with the expressive agent, the other with the affective features of the output disabled (randomly). The user interacts with the SAL agent's presented in a computer screen (only the face is rendered), using the available cameras and microphones.

Discussion There is evidence that expressive abilities may substantially impact the interactions between humans and agents by denoting that flow and perceived engagement was much higher in the emotional SAL than in the control environment. Compared with previous described systems, it is one of the most complete models for managing backchannels and turn taking strategies, however, as stated previously in Section 2.1, attentiveness and coordination are not enough to build rapport, it is also necessary to stimulate positivity which this system does not cover. To conclude, the most relevant aspects of the systems are:

- Generate good listeners without understanding semantically what it is being said;
- Parallel independent action proposers that uses both rule and ML approaches;
- Dedicated dialogue management models;
- Covers several users affective states by modelling distinct characters.

3.4 Learning Social Behaviour from Wizards

More recently, researchers are proposing to use WoZ studies to train virtual agents [22, 24]. In WoZ studies [61], subjects are led to believe that they are interacting with an autonomous robot when, in fact, they are interacting with a human (the wizard). However, when applying WoZ in learning environments [24], robots possess limitation and constraints over their perceptions and actions that the human expert (the wizard) does not have. For this matter, Sequeira et al., developed a novel approach, based on WoZ, that restricts the wizard's perceptions over the environment and the behaviours it controls according to the agents' inherent limitations.

Procedure Description Following Figure 6, the development design is separated into three stages: *Data Collection*, *Strategy Extraction*, and *Strategy Refinement*.

In the first stage, *Data Collection*, mock-up studies are conducted to gain expert knowledge of common patterns in the target scenario. From the collected information, the set of all perceptions and possible actions (shared between the agent and the wizard) will define the *Task AI* module.

From the previous mockup and WoZ studies, in the *Strategy Extraction* stage, a *Hybrid Controller* that will guide interactions is developed, containing:

- ***Rule-based module***: defines high-level interactional rules that are triggered by simpler perceptual. E.g., summarise student's progress at the ending of the session;
- ***ML-based module***: using ML classifiers, it handles more complex situations, that may emerge during the sessions, that are harder to specify using behaviour rules.

The *Hybrid Controller* has the same responsibilities as the wizard: deciding when and which behaviour to trigger.

In the last stage, *Strategy Refinement*, HRI researchers evaluates the generated interaction strategies to refine the agent's behaviours for situations that may not have been properly learned or, for situations that require more relevant information.

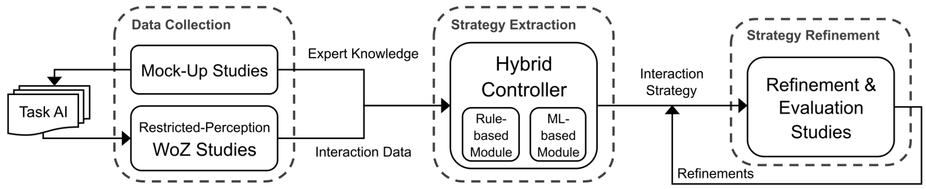

Figure 6: Different stages of the methodology for discovering interaction strategies from restricted-perception WoZ studies. From [23].

Evaluation The proposed methodology was tested using a autonomous humanoid tutor capable of learning with young learners in a multiplayer turn-based collaborative video game for building sustainable cities [62]. The authors compare the fully-autonomous hybrid controller and a standard unrestricted WoZ robot regarding empathy using Interpersonal Reactivity Index (IRI) [63], anthropomorphism, animacy, likeability, perceived intelligence and perceived safety of robots using Godspeed series [64], and engagement using task-related questionnaires.

Discussion The results showed that empathy was perceived similarly between all conditions but the unrestricted WoZ interaction strategies were preferred. The perceived intelligence and security were slightly higher in the restrictive WoZ, and the restricted-perception WoZ based robots were able to engage very naturally in socially-aware interactions.

This approach requires more preparation than the unrestricted WoZ and, as the author suggests, even by using restrictive WoZ, it is difficult to isolate the human expert's implicit knowledge regarding the environment.

To conclude, the most important aspects that may contribute to the proposed solution are:

– Use of mockup-studies to gain preliminary insight of common patterns in human behaviour;
– Restricting the wizard's perceptions to the same extent as the agent;
– Use of an iterative approach to further refine the model in each iteration;
– Hybrid controller with rule-based and ML-based modules for simple and more complex perceptual states, respectively;
– Usage of thinking aloud technique to gain further insight on the users [65].

3.5 Overall Discussion

Developing a computational models capable of managing rapport similarly to humans is not an easy feat. Researchers had to focus their research on different aspects of rapport and assess their overall contribution. Table 3 and Table 4, respectively, compares the systems regarding how they learn social behaviours, and the used rapport management strategies.

Current literature suggests continuing the research on learning social behaviours from WoZ [19, 23, 24] studies and use primarily RL [16–19] classifiers

	Type	Agent	Gaze	Backchannel	Small-Talk	Facial Expressions	Gestures	Mirroring	Smile	Turn Taking	Praise
Mutlu et al. [22]	Rule-based	Robotic	✓	✗	✗	✗	✗	✗	✗	✗	✗
Stanton et al. [47]	Rule-based	Robotic	✓	✗	✗	✗	✗	✗	✗	✗	✗
Andrist et al. [21]	Rule-based	Robotic	✓	✗	✗	✗	✓	✗	✗	✗	✓
Mohammad et al. [48]	ML-based	Robotic	?	✓	✗	✗	✗	✗	✗	✗	✗
Huang et al. [52]	ML-based	Virtual	✗	✓	✓	✓	✓	✓	✓	✗	✗
Kok et al. [17]	ML-based	Virtual	✗	✓	✗	✗	✓	✗	✗	✗	✗
Schröder et al. [60]	ML-based	Virtual	✗	✓	✗	✓	✓	✗	✗	✓	✗

Table 3: Brief comparison regarding how different virtual agents manage strategies. The systems presented here appear in the same order as in the main body of the text. ✓, ✗ and ?, represents whether the specified strategy is applied, not applied or unclear, respectively.

(Section 2.3). This class of algorithms are applicable in rapport as there are sequences of states that will help the agent to know when and how backchannels should be produced in order to build rapport (the reward function). In addition, authors suggest developing solutions capable of adapting current course of actions to the current context of the interaction to improve the quality of virtual agents during interactions [38, 43–45].

System	Training Source	Iterative
Mohammad et al. [48]	Direct Samples (Unsupervised)	Yes
Virtual Rapport 2.0 [52]	Corpus	No
Iterative Perceptual Learning (IPL) [17]	Corpus & Subjective evaluation	Yes
Sensitive Artificial Listeners (SAL) [60]	Corpus & WoZ	Yes
Restricted Perception WoZ [23]	WoZ	Yes

Table 4: Brief comparison of methodologies to learn human social behaviours.

Most of all, the communication goals of interactions must be considered when developing rapport agents. The context in which the communication partners will interact, the inherent limitations of the virtual agents' perceptions and actions and, most importantly, what kind of emotions and actions we want to elicit from the conversational partner are crucial for the development of such agents. For example, in tutoring applications, mutual gaze plays an important role for increased learning performance [66–68], and in negotiation scenarios not reciprocating negative self-disclosure has ben shown to destroy rapport [69].

4 Proposed Solution

The current section describes the proposed solution that will address the development of a robotic rapport agent that improves current models for generating backchannels in dyadic interactions. Following current literature, the solution will inspire on the hybrid system described in Section 3.4, on perceptual readings to refine ML models described in Section 3.3.2, on the WoZ novel approach for training ML classifiers described in Section 3.4, and, to a lesser degree, current work on iterative systems capable of adjusting their current course of actions in real time [38, 43–45] (Section 3.1).

Section 4.1 briefly describes SERA framework that is currently embed on several robotic agents and will support the proposed solution. Section 4.2 describes the rapport agent system architecture and Section 4.3 describes the proposed method to train the system in order to produce correct backchannels during the interactions.

4.1 Supporting Technology

In the research community there are several frameworks to ease the development of virtual agents in HRI by promoting reusability between components. Examples of frameworks include SEMAINE [70], Virtual Human Toolkit [71], Artificial Social Agent Platform [72], Robot Behaviour Toolkit [73], and SERA [15]. The solution will choose the latter as it is being developed internally in GAIPS, is used extensively in several HRI studies [15], and was tested in several different embodied robots such as EMYS (Figure 7) and Keepon (Figure 8).

Figure 7: EMYS robot.

Figure 8: Keepon robot.

SERA follows the SAIBA model [46] and is very similar to Robot Operating System (ROS) [74] due to, respectively, the separation between intention planning, behaviour planning and realisation, and due to the usage of decoupled modules in an asynchronous messaging system. It aims to be used by both technical and non-technical developers such as psychologists [15], an advantage as their knowledge is crucial during the development and analysis of HRI. For example, utterances are modelled using markup text that can contain non-interrupting behavioural rules and can be developed by non-technical teams.

The most important components are Thalamus, Skene and Nutty Tracks.

- ***Thalamus***: responsible for receiving and delivering the published messages to the right subscribers;
- ***Skene***: responsible for translating high-level intentions generated at the decision-making level into a schedule of behaviour actions;
- ***Nutty Tracks***: responsible for managing animations.

Skene is the most relevant component in SERA for the development of rapport agents as it is the controller that plans animations and non-verbal behaviours such as gaze, utterances and animations according to perceptual messages. This component is rule-based and has an explicit representation of its body position over his physical environment.

SERA also includes modules for bridging external tools such as Fearnot AffecTIve Mind Architecture (FAtiMA) to model emotions [75] or Unity to create virtual scenarios. All these modules co-exist inside the *Thalamus* "network" to cooperate, in order to achieve the interactional goals in any HRI scenario (e.g., negotiation scenarios on Figure 9).

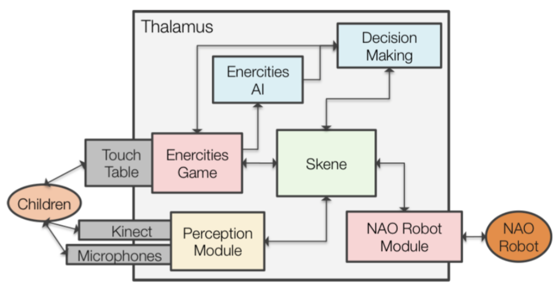

Figure 9: Enercities scenario system architecture integrated with SERA framework. From [15].

Despite being under development, SERA is stable and demonstrates its applicability in a wide range of HRI scenarios. However, the *Skene* component lacks rapport management strategies and it does not adapt its actions when interrupted by the user, which reduces coordination and the overall feeling of rapport. Moreover, the *Skene* component is rule-based which is not sufficiently elegant to build systems more appealing and natural to end-users.

4.2 Architecture

In order to evaluate the proposed backchannel behaviour generation ML classifier we require a robotic rapport agent to be tested on human subjects. We propose extending SERA framework to manage rapport by providing tools for stimulating positivity, coordination, and mutual attention (similar to Figure 1 on Section 2.1) enabling flexibility, and reusability in different scenarios. Despite backchannel behaviours being more targeted to enhance mutual attention and coordination, we intend to stimulate positivity as well, by using specific interactional rules.

The architecture that will instantiate the above proposal is depicted in Figure 10. The system decision making process is managed by the *Rapport Controller* Module that contains three components: a rule-based and two ML-based components.

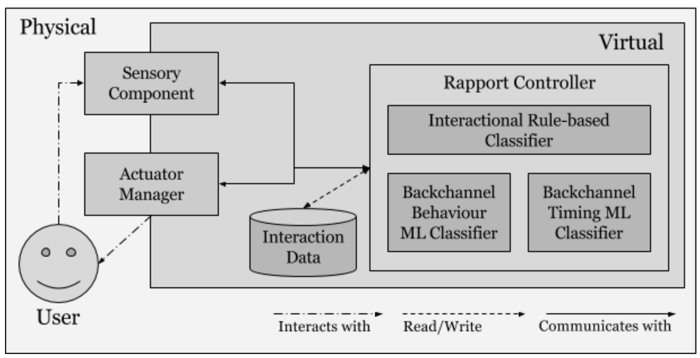

Figure 10: Partially decided Rapport Architecture proposal.

The rule-based component is responsible for managing high-level interactional rules that are easier to specify, for example, compliment cooperation actions to stimulate positivity. These rules can be either context specific, or generic enough to be included in other scenarios. The *Interactional Data* data storage depicted in Figure 10 containts relevant information to manage the interaction.

Two ML-based components will handle more complex perceptual states that may arise during the sessions and that would be hard to explicitly define behavioural rules. One module will return correct timings for the generation of backchannels and the other will return the most fitting backchannel behaviour. For example, the first module will suggest that the current instance is appropriate, and the second module will return head nod as the most adequate social behaviour. The retrieved features should be as context independent as possible, including features such as facial expression, head nod frequency, presence of a smile, silence duration, and gaze position. The dominant ML classifier is Reinforcement Learning (RL) (Section 2.3) as it was suggested by several authors [16–19].

The *Rapport Controller* will redirect perceptual information collected from the *Sensory Component* and *Actuator Manager* to its component, and will analyse the returned result. From it, the controller will decide which actions should be initiated, maintained or even interrupted. With the bidirectional relationship between the *Rapport Controller*, the *Sensory Component*, and the *Actuator Manager*, we aim to extend SERA to support interruptible actions and allow quick adjustments to the agent's behaviour and build better rapport [38, 43–45]. For example, similarly to the agent described in Section 3.3.1, interrupting current speech acts whenever the user starts to speak.

Conflicts may arise between the rule-based component and the ML-based components. If the generated behaviours do not conflict with each other, e.g. gaze target and smiling, both actions are executed by the agent. If the generated behaviour conflicts with another, then the ML-based components take priority over the rule-based. If there is conflict between two rules, the one with the highest priority takes place (e.g., silence over vocalisation when detecting user's speech).

4.3 Learning Subconscious Behaviours

Both ML-based modules proposed in Section 4.2 need to be trained in order to learn how to generate correct backchannels. Note, as mention in Section 3.4, that in WoZ the human subject is not aware that the agent is being controlled manually (partially or fully) by another human, the wizard. In the traditional WoZ, the wizards have full access to what is happening in the scenario and have control over the virtual agent, using a User Interface (UI). However, as aforementioned by Sequeira et al., it is relevant to take into account that the virtual agent has inherent limitations in their perceptional abilities and their actions onto their external world [23]. Moreover, social behaviours are mostly done subconsciously, therefore, the experiment could be influencing the results by just forcing the user to rationalise over what is being subconsciously felt. Taking this two issues into account, we propose an approach for learning correct backchannel generation in virtual agents and embodied agents in HRI using limited-perception WoZ and human experts for corrective feedback (Figure 11).

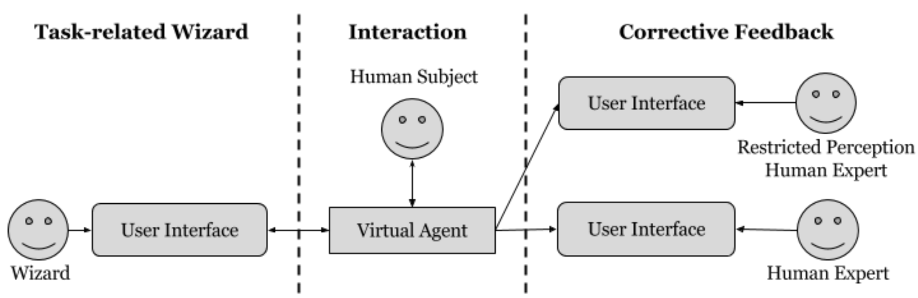

Figure 11: Using perceptual readings and limited perception WoZ to assess backchannels quality. Human experts monitor the interaction and provide corrective feedback according to their perceptions. The task-related wizard is optional.

Following Figure 11, one wizard is responsible for controlling the virtual agents task-related actions and two human experts for providing corrective feedback regarding whether the agent's behaviour is socially appropriate or inappropriate [17, 58], using a UI. One human expert will have its perceptions limited with same extent as the virtual agent, and the other will have unrestricted perceptions. This approach can be seen as reverse-RL since it is possible to map the human experts feedback to a reward function, in which, appropriate and inappropriate backchannels will have values values 1 and -1, respectively.

Using this approach it is possible to obtain multiple feedback over the generated behaviours, similar to PCS [57] without influencing the results by forcing the users to rationalise their actions. Cohen's kappa coefficient κ may be used to measure inter-rated agreement between two human experts (Equation 5). In the equation, p_0 is the relative observed agreement and p_e the probability of random agreement.

$$\kappa = \frac{p_0 - p_e}{1 - p_e} \tag{5}$$

With the data collected using the restricted-perception WoZ, the data will be pre-processed and used to train the ML-based component using Weka [76]. RL algorithms will take priority since they were the main suggestion from several authors [16–22]. Nevertheless, similar approaches can be further investigated.

As summarised in equation 6, the system evolves as follows. The initial version M_0 is the only version that is strictly rule-based and stripped of previous knowledge according to the information collected from preliminary studies, and the interactional goals. The goal of M_0 is to explore as many state combinations as possible in order to produce great number of backchannels, and acquire, as much corrective feedback as possible from the human experts [17]. The corrective feedback collected on M_n is later used to train M_{n+1} version of the rapport agent. Following this pattern, we expect M_n to build better rapport than the previous M_{n-1} version. Note that, after the first learning state, the initial excessive backchannels rules must be discarded and replaced by the ML generated backchannels, similar to how IPL (Section 3.3.2) discards the negative samples after the first subjective evaluations.

$$M_{n+1} = M_n + Corrective\,Feedback \tag{6}$$

To conclude, after several iterations [17, 23], the best possible model M_n will be one tested on users, in which human experts are not required to be present since the agent does not benefit from further training. The final system should represent the average listener's behaviour interacting with the average speaker. Preliminary studies may be conducted to assess the feasibility of the proposed learning strategy.

5 Evaluation

The current section will describe the methodology that will be used in order to evaluate the correctness and benefits of the proposed solution.

The proposed solution aims to improve current backchannels models and test the developed model on a robotic rapport agent. Robot EMYS will be used due to its expressiveness, and the negotiation scenario will be simplified version of Split Or Steal [77], due to its simplicity and because it was previously integrated in the SERA framework. Split Or Steal requires two players that will discuss how a large amount of money will be shared among the players. After a brief initial discussion, each player will have to choose one of two spheres that will decide the outcome of the game: *Split* or *Steal* (Table 5).

Player1/Player2	***Steal***	***Split***
Steal	$0, 0$	$2, 0$
Split	$0, 2$	$1, 1$

Table 5: Split Or Steal payoff matrix. Both players lose the money if they both decide to *Steal* and the money is divided in half if both players decide to *Split*. The remaining options leads to the *Steal* player keeping all the money.

The evaluation of the proposed solution must into three main issues:

- Correctiveness of the generation of backchannel behaviour;
- User preference of the trained system over the untrained version (rule-based);
- Assess the impact of rapport in cooperation in negotiation scenarios.

We will investigate previous literature to assess what are the most important features and interactional rules in these types of games. With this knowledge we will define what are the set of actions and perceptual capabilities that EMYS should have to be successful in building rapport, and define the initial version of the system, M_0, solely rule-based and and stripped of previous knowledge. The baseline for evaluation will be a lighter version of M_0 that tries to balance when and how to generate backchannels without the eagerness to generate more backchannels in order to have more corrective feedback.

The evaluation process will focus on studying how version M_n represents an improvement over previous version M_{n-1}. Human subjects (at least 30 from the university to ensure statistical viability) will interact with the version M_n of the rapport agent (with $n = 1, 2, ..., n$) while human experts (from the research group) provide corrective feedback. After each session, each person will answer a questionnaire in order to evaluate their individual experience. This questionnaire aims to measure the users perception of rapport on the embodied agent using:

- Adapted version of Interpersonal Reactivity Index (IRI) [63];
- Godspeed series [64];
- Five-item social presence scale [54];
- Engagement using task specific questionnaire.

The inter-rated agreement between the human experts will be measured using Cohen's kappa coefficient (Equation 5) and the the trained models will be objectively measured for precision (Equation 1) and recall (Equation 2). The initial RL values (Equation 4): learning rate α, discount value γ, and the initial reward function $R(s_t, a_t, s_{t+1})$ will be studied to verify which combination leads to better results (Section 2.3).

Lastly, we expect the last version of the system, M_n to be able to build rapport, provide better backchannel feedback and elicit more cooperation from the users in the negotiation scenario.

6 Conclusion

The state-of-art in rapport agents suggests that it is very difficult to implement a computational model capable of managing rapport similarly to humans. However, by restricting such models, it is possible to create imperfect systems that are capable, at some length, to increase rapport between agents and humans. There are not many agents with data-driven components for managing rapport in Human-Robot Interaction. Most of the ML-based current agents use data-driven classifiers to improve their task performance and not, as we intend, improve their social behaviour performance.

The current state-of-the-art covers two classes of systems. On one hand, rule-based systems are easier to develop but are more rigid, on the another, ML-based systems are more effective on generating behaviours that are perceived as more natural by humans. Moreover, some authors have been working on continuous interaction systems that are capable of interrupting or even adapting their current set of active actions. Other researchers have been working on agents that pro-actively seek task-related information to complement their knowledge and improve their results.

The proposed solution aims to create a robotic rapport agent that takes the best of both rule-based and ML-based systems, and a novel approach for learning backchannels using restricted-perception WoZ and human experts for corrective feedback. Following the tendency and suggestions made by researchers, we will use RL as the dominant classifier (albeit other classifiers may be considered) and we will repeat the learning stage until there are signs of convergence. The developed solution will be internally incorporated in SERA framework that is being actively developed in GAIPS, has been used extensively to conduct several studies and it is well integrated with EMYS.

To assess the performance, the untrained system (rule-based) will be compared with the trained system in a negotiation scenario, Split Or Steal using robot EMYS. We expect the backchannel model, and therefore the rapport agent, after some iterations, to be able to produce more natural backchannels than the untrained system, and elicit more cooperation from the adversary by building rapport.

The development of the proposed work will follow the schedule presented in Appendix A.

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Appendices

A Planning