Dyads to Groups: Modeling Interactions with Affective Dialog Systems

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ABSTRACT: *Affect Listeners[2] are applied as tools for studying the role of emotions in online communication. They need to interact both in dyads as well as in group settings with multiple users. In this paper, we present the evolution of such affective dialog systems from a focus on dyadic interaction to multi-party interaction on chat networks. Starting from experiments on the use of these dialog systems in virtual dyadic settings, we outline the requirements, design and implementation decisions necessary to apply the systems to affective interactions with multiple users. Finally, we introduce two realisations of Interactive Affective Bots designed for such interaction scenarios that integrate modelling of individuals and groups as part of their decision mechanism.*

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1. Introduction

The project CyberEmotions[3] deals withmodelling and understanding of the role of *collective emotions* in creating, forming and breakingup of online-communities. As part of the Cyberemotions project, the development and experimental evaluation of affective dialog systems that interact with users of network communication channels is undertaken [38, 31]. These systems serve two purposes: i.) a study tool for investigating the role of emotions in online communication and affective human-computer interaction, ii.) a support tool for ecommunities providing online analysis, simulations and predictions for group dynamics, in particular addressing their affective dimension.

To date, Affect Listeners were applied in a range of experiments in dyadic settings which served to evaluate the systems' ability to participate in a realistic and coherent dialog and to establish and maintain an emotional connection with a user; and extended the understanding of the impact of affective system profiles and fine-grained communication scenarios on the self-reported emotional changes of users, their communication style and textual expressions of affective states. The next step, the application

[2] This article is an extended version of the paper: M.Skowron, S.Rank, "*Affect Listeners - From dyads to group interactions with affective dialog systems*", presented at LaCATODA, AISB/IACAPWorld Congress 2012 [42].

[3] http://www.cyberemotions.eu/ (all URLs last accessed 2012-12-12)

of such systems to group interactions created a new set of challenges related with, e.g., simultaneous communication with multiple users, capacities to interact in a way which intentionally follows or violates the typical communication patterns of members of a particular e-community, including the affective dimension of such interactions, or the ability to observe such a behaviour in other participants. These functionalities impact the system's ability to generate consistent or intentionally inconsistent interactive behaviour, the required affective coherence and the event-dependent adaptation of its communication patterns to other members in a group. In parallel, the system needs to represent and model discussions and emotional exchanges, at the individual and group levels, to provide the foundation for predicting the possible outcomes of the observed group dynamics, for simulating the effects of system's interactions with individuals or a group, and finally to assess the real effect of its interventions and to correspondingly update the used models.

To address the requirements related with transferring Affect Listeners from dyadic to multi-user interaction settings, the proposed approach integrated experience gathered in experiments in dyadic settings with insights acquired from a wide range of studies on the role of emotions in online communication: psychological studies and experiments on perception and generation of emotionally charged online content [17, 19], agent based models of emotions [37, 7], valence trends [4], agent based model on bipartite networks [23, 11], and event-based network discourse analysis [15]. Potential applications of such systems include support tools for online communities, e.g., providing information on the current affective state of groups, or forecasting the changes in groups' affective states or interaction dynamics.

In the remainder of the paper, we present the concept of Interactive Affective Bots (IAB) and an overview of experiments with one of the system's realization in dyadic settings. Next, based on the experiences with Affect Listener systems obtained in dyadic interaction settings and modelling of affective interactions in e-communities, we outline the requirements, design and implementation decisions necessary to apply the systems to affective interactions in multiple users environments. Finally, we introduce two realisations of IABs designed for such interaction scenarios that integrate modelling of individuals and groups as part of their decision mechanism. We conclude by discussing the relevance of the presented approach to the goals of the Turing Test, and discuss new challenges and opportunities related with the application of artificial systems for interactions and cooperation in online environments that include large number of users.

2. Interactive Affective Bots

The specifics of online, real-time and unrestricted interactions with a wide range of users influenced the selection of methods and design decisions in IAB. In particular, we aimed at: (i) robustness regarding erroneous natural language input, (ii) extensibility regarding system components and application scenarios. (iii) responsiveness; both for the generation of system responses and for simulations of individual users' and collective emotions of the e-communities. Below we provide an overview of the main system components. For a detailed description of the system architecture and components used refer to [38, 41, 43]. At the top level layer, each realisation of IAB share the same structure, which includes Communication, Perception and Control layers presented in Figure 1.

The Perception Layer, cf. [40], annotates both user utterances and system response candidates. This includes sentiment class and negative/ positive sentiment strength [26]; valence, arousal and dominance [3]; various linguistic, cognitive and affective categories from the LIWC dictionary [28]; dialog act classes [39].

The Control Layer manages the dialog progression by relating observed dialog states to intended ones (e.g., querying and follow-up questions on the user's affective states, realizing a particular communication scenario) using the cues provided by the Perception Layer. This layer selects the system response from a number of generated response candidates, integrating rule-based action selection - Affect Listener Dialog Scripting (ALDS) - with the command interpreter for the task specific Affect Listener AIML-set[4]. As detailled in this paper, the control layer also integrates modelling of users, individuals as well as groups such as chat rooms, as part of its decision mechanism.

The Communication Layer handles the reception and dispatching of user/system utterances and provides the system with an interface to a range of interaction environments such as: Web Chat, 3D event engine[13], ICQ, XMPP (Jabber, Google or Facebook Chat). The specification of an IAB includes the following layers of perception and interaction analysis:

[4] Artificial Intelligence Markup Language (AIML)

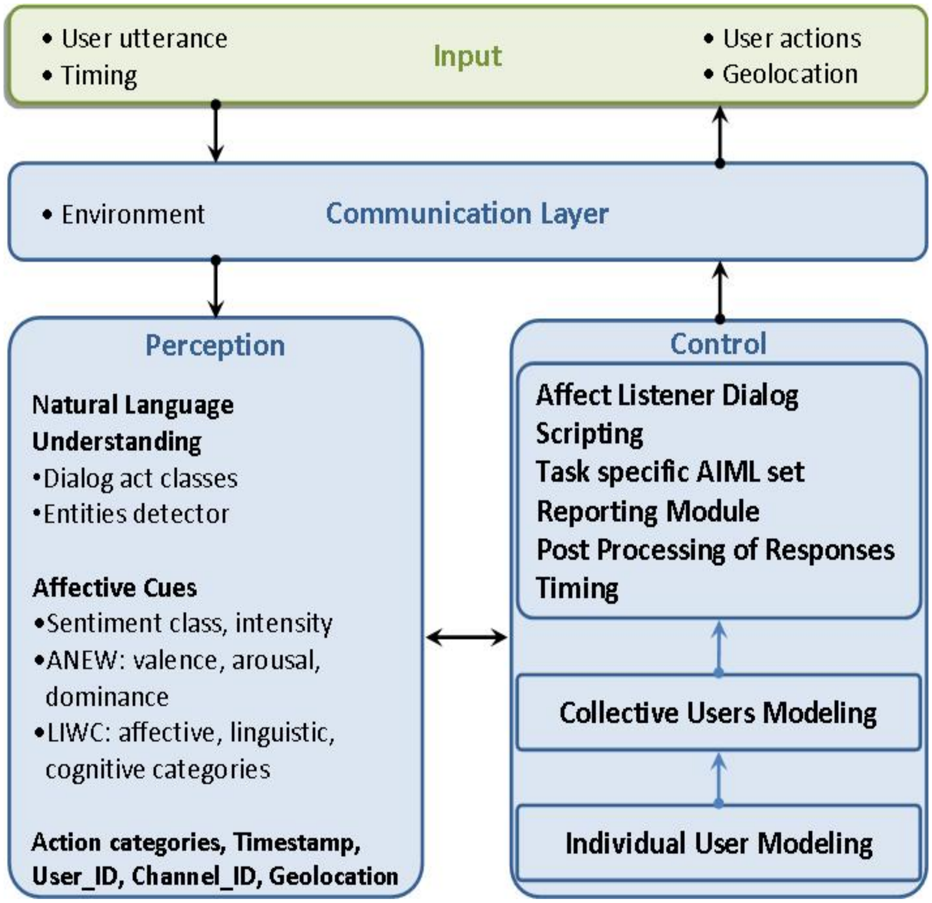

Figure 1. Interaction loop and generic architecture of Interactive Affective Bots

1. Single utterance: annotation based on the Input Perception tool, a set of rules for generating system responses (Input Processing, AL-AIML [40])

2. Ongoing conversation: perception and analysis of the conversation context, tracking of effects of previous utterances (Input Processing, ALDS [38])

3. Individual and collective user modelling: long-term communication patterns or "*personalities*" of users regarding their textual expressions of affective states, characteristics of interaction patterns and sentiment expressions of groups of users and user populations (CybABMod - see section 4.4)

2.1 Dyadic Interactions - Dialog Participant

The Dialog Participant realization of IAB is primarily applied for managing text-based communication with a user in an online, 1-on-1 interactive environment. It analyses and responds to the changes of the user's emotional state, i.e., textual expressions of affective states detected in the user's utterances. The typical objectives for the system in this interaction scenario include:

1. Realistic and coherent dialogs,

2. Conducive setting for communication (i.e. acquisition of large data sets),

3. Task-oriented dialogs related to "*hot topics*" in order to acquire users' affective states and stances towards the issues,

4. Studying the role of emotions in 1-on-1 HCI, e.g., the ability to consistently generate a particular affective profile and analysing its impact on users' self-reported emotional changes or textual expressions of affective states; or to convincingly realize a specific communication scenario, e.g., "*getting acquainted with someone*", "*social sharing of emotions*", throughout the whole time-span of communication with users and measuring their effects on users' communication patterns or their influence on system evaluation results.

3. Experimental results - Dialog Participant

3.1 System evaluation in a Wizard-of-Oz setting

The first round of experiments was conducted in a Virtual Reality environment (see [13] and [41] for more details on the evaluation), where the dialog system was compared with aWizard-of-Oz setting (WOZ)[5], in terms of its ability to: establish an emotional connection, dialog realism, and providing an enjoyable chatting experience. After each of the experimental interactions, participants were asked the following questions for assessing the dialog system, represented as a Virtual Human (VH):

1. Did you find the dialog with the VH to be realistic?
2. How did you enjoy chatting with the VH?
3. Did you find a kind of emotional connection between you and the VH?

The results achieved by the dialog system matched those obtained for the WOZ condition, i.e., there was no significant difference between the two settings.

3.2 Impact of system's affective profile

We define *artificial affective profiles* as a coarse-grained simulation of a personality, corresponding to dominant, extroverted character traits, that can be consistently demonstrated by a system during the course of its interactions with users [43]. In a second round of experiments, three distinct affective profiles were implemented in the dialog system: positive, negative and neutral. Each affective profile aimed at a consistent demonstration of character traits of the system that could be described as:

- cooperative, emphatic, supporting, positively enhancing, focusing on similarities with a user - (positive),
- conflicting, confronting, focusing on differences - (negative),
- professional, focused on job, not responding to affective expressions - (neutral).

In these experiments, a browser-based communication interface, resembling a typical web chat-room environment was developed: a user input field at the bottom of the screen and a log of communication above. Participants interacted with the IAB in an unsupervised manner and were aware that they talk with an artificial system.

The results, presented in more details in [43], demonstrate that the implemented affective profiles to a large extent determined the assessment of the users' emotional connection and enjoyment from the interaction with the dialog systems, while the perception of core capabilities of the system, i.e. dialog coherence and dialog realism, were only influenced to a limited extent. Further, the self-reported emotional changes experienced by the experiment participants during the online interactions were strongly correlated with the type of applied profile. The affective profile also induced changes to various aspects of the conducted dialogs, e.g., communication style and the users' expressions of affective states. These results suggests that the participants, under this condition, assumed a more open, positive, sharing oriented attitude [44], which is also in line with the theory on Interpersonal Complementarity [18], which suggests that people in dyadic interactions negotiate their relationship through verbal and nonverbal cues, where dominant-friendliness invites submissivefriendliness whereas dominant-hostility invites submissive-hostility, and vice versa.

4. Scaling up to multiple users environments

4.1 Goals of IABs in multiple users environments

The experiments described above demonstrated that in the presented evaluation settings (VR or online web chat, relatively short interaction time) the system is able to conduct a realistic, enjoyable interaction and to establish an emotional connection with a user matching the results obtained in theWOZ setting. Further, the application of affective profiles showed an effect on self-reported emotional changes experienced by participants during the interaction with IABs, influencing also the textual expression of affective states and, to a smaller degree, the perception of core functionality of the artificial interlocutor, i.e., dialog realism and coherence.

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[5] Participants believe that they communicate with a dialog system, while responses are actually provided by a human operator. In the presented experiments, the operator was asked to conduct a realistic and coherent dialog and provided free text input to user utterances.

The systems targeted at multi-user environments are primarily focused on supporting these e-communities by providing information - on demand or time-based - about a group's interaction dynamic, affective state, outcomes of the simulations regarding those parameters and exhibit relatively low activity levels in terms of direct communication with users. For groups, an IAB can track both content and affective dimensions of the communication between multiple users.

4.2 Role of simulations in IAB

The role of agent-based modelling and simulation in this kind of interactive system is two-fold: to provide part of the information provided to participants and to serve as decision support. Based on a request from a particular online community the tools can support it with analysis on affective dimension of their interactions and provide suggestions on ways for counter-acting negative tendencies observed in a group, e.g., a decrease of cooperation or growing hostility between members. Further, simulation results can indicate targets for interventions. This entails several requirements that concern both the results of simulation runs as well as runtime characteristics and the adaptability of the simulation based on data collected during previous interactions. At this level, several questions relevant as a potential input for the systems' decision making mechanisms were identified [31]:

- Which individual in a group will be most likely to provide an accurate response to probing about the group's emotional state, and which one will be most reliable?
- What influence can individuals have on the evolution of the collective emotions in an e-community, and which of the specific participants is likely to have the biggest influence?
- Can potential escalations, both in the negative and in the positive direction, be detected early on?
- What influence will a specific intervention of the system have at the current moment, and which style of intervention is most effective?

Running a simulation on demand to query about the above questions adds the requirement of timely, or possibly anytime, responses but also the need to parameterise the simulation to quickly adapt to the current state of an e-community, ideally using the recorded history as input.

An important part of the decision-making structures of IABs is the modelling of conversation participants. This component of the agent control structure is analogous to adaptive user modelling in standard Human-Computer Interaction: the system initially has a default model of the interaction partner, adapts it over time, and complements missing information based on the knowledge derived from interaction events. In the case of multi-user environments, this includes modelling several participants, simplifying the employed models and abstracting from specific individuals.

The modelling eventually serves the purpose of deciding on utterance selection, utterance modification, timing of utterances, and the selection of conversational partners in multi-user environments. As such, the main questions that modelling efforts helps to answer for the purposes of affective interactive systems are, from general to specific:

1. What potential influence will certain interventions have on the collective state of an online community?
2. What is the influence of particular interventions on the future development of a specific group?
3. What type of intervention (affective charge, topic, timing) will have which effect?
4. What relation does a particular individual have to the state of a specific group?
5. Which intervention is most appropriate when addressing a particular individual of a specific group?

4.3 Input from theoretical modelling and analysis

The questions enumerated above relate the decisions of individual agents to the collective emotions of the group, and require a special approach that can deal with the relation between individual and collective levels. The simulation of emotions in our system is based on the modelling framework for collective emotions in online communities [37]. This framework, based on the concept of *Brownian agents* [36], allows the integration of empirical results, and shows the emergence of collective emotional states from the interaction of many users in an online community. This framework has been applied to different types of online communities, including product reviews communities [9], social networking sites [47], and blogs [22]. Within this framework, a particularly relevant application for IABs is the model for emotional persistence in online chatting communities [7], which provides a description of individual emotion dynamics for the users of a real-time group discussion. The emotion dynamics in our dialog system will be driven by this model of chat-room discussions, which we refer to as *Brownian agents model*.

4.3.1 Activity patterns in time

Based on the analysis of Internet Relay Chat (IRC) data[6], the dynamics of the Brownian agents model are based on empirical analysis of user interaction in real general discussions. The statistical analysis of that data shows an activity pattern in the moments when users create messages in the group discussion. Figure 2 shows the distribution of time intervals between messages of the same user, aggregated for all users and all discussions. Similar as for the case of SMS communication [48], this distribution has two modes, one corresponding to the time intervals between bursts of interaction (red), and another one containing the time intervals within an interaction burst (green). The latter is characterized by a power-law distribution of the form $P(\Delta t) \sim \Delta t^{-\alpha}$ for $\alpha = 1.54$, where the former is better explained by a lognormal distribution.

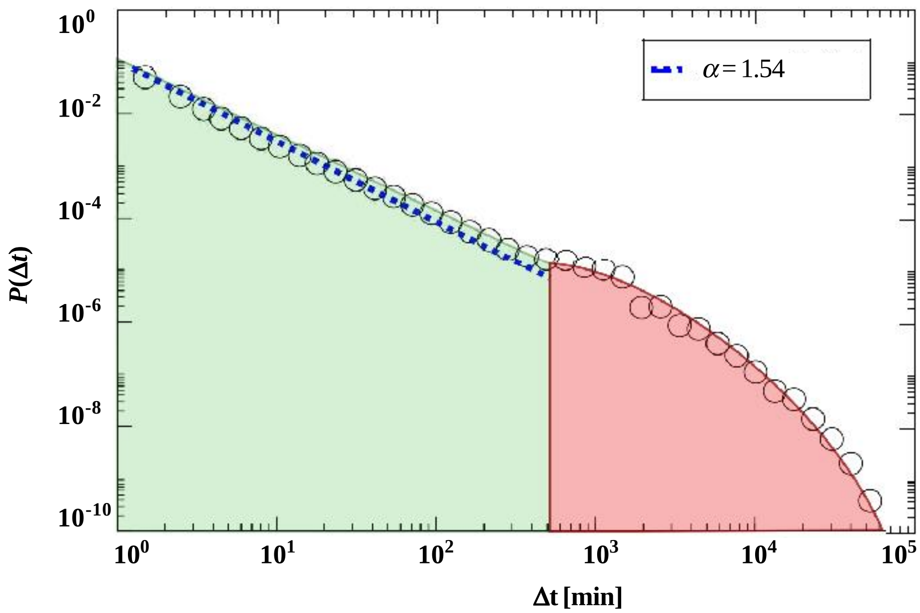

Figure 2. Empirical distribution of time between messages of the same individual. [7]

To provide the most realistic behavior possible, the Brownian agents model is driven by events following this empirical distribution. For the case of IABs, every reaction will have an additional delay Δt, sampled from the power-law regime of the distribution, i.e. the inter-activity times associated with group discussions. The addition of this additional stochastic delay changes the properties of the dialog system in a substantial manner that is commonly ignored in this kind of systems. A usual design decision driven by intuition is assuming that the time between messages of an agent can be sampled from a distribution with a given mean (e.g. normal). On the other hand, the empirical distribution of time intervals between messages in a group IRC discussion is very different, following a power-law of exponent 1.54, which does not have a finite first moment. Therefore, empirical evidence contradicts the assumption mentioned before, and our IABs will have a time behavior closer to the real patterns in online interaction.

It is worth to mention that this kind of distributions have been found in other kinds of human communication [25, 20], and can be explained by priority patterns in dealing with communication tasks. In particular, a power-law with exponent close to 1/2 is characteristic for low-priority communication, in which the rate of incomingmessages is higher than the rate of individual responses. Our model incorporates this kind of "*procrastination*" component, which seems to be one of the driving mechanisms behind online communication.

4.3.2 Emotional persistence

Among the affective cues mentioned above, sentiment analysis techniques can extract the emotional content of short chat-room messages, giving a value of polarity per message. This way, a sequence of messages would be represented as an ordered set of

[6] Analysed data-set included 2.5 million posts acquired from EFNET IRC chats: http://www.efnet.org, covering a range of topics including music, casual chats, business, sports, politics, computers, operating systems and specific computer programs.

ones for positive messages, zeroes for neutral messages, and minus ones for negative messages. When large enough, these kinds of sequences can be processed with tools from statistical physics, revealing properties of the emotions expressed at individual and group levels. One of these techniques is called Detrended Fluctuation Analysis [27], which can be used to calculate the Hurst exponent [16, 34], a measure of persistence in a time series. This persistence is reflected in the time series as consistent fluctuations around its mean, revealing states of consistent biases towards positive or negative emotions.

Persistence can be calculated for an individual user, when processing the sequence of emotional expressions of that user, or at the discussion level, when computing it over all the messages in a group discussion. If a user behaves in a fully random way, with fixed probabilities of each sentiment polarity but no memory, it would have a persistence of 0.5 and a mean emotional expression according to the given probabilities. A user with a tendency to express emotional states more similar to the previous ones, would have a persistence above 0.5, revealing a memory of the emotion, or some momentum of emotional expression. This case of persistent users is the most common one, which can be appreciated in the kernel density plot of Figure 3 in combination with the distribution of mean emotional expression. Most of the users show a bias towards positive emotional expression, with persistence in the way these emotions are expressed though the discussion.

As mentioned above, persistence can be calculated at the discussion level too, analyzing the collective emotions in a group of users. The empirical analysis of 20 IRC channels [7] showed persistence values above 0.5 for all channels, revealing the existence of collective emotional states at the aggregated level. This appears in the discussion as fluctuations around the mean emotional content, which is also in general biased towards positive emotions. This collective positivity and persistence shows that users influence each other through their expression of emotions, and that certain rules of emotional expression are present even in the anonymous and ephemeral discussions of IRC chat-rooms.

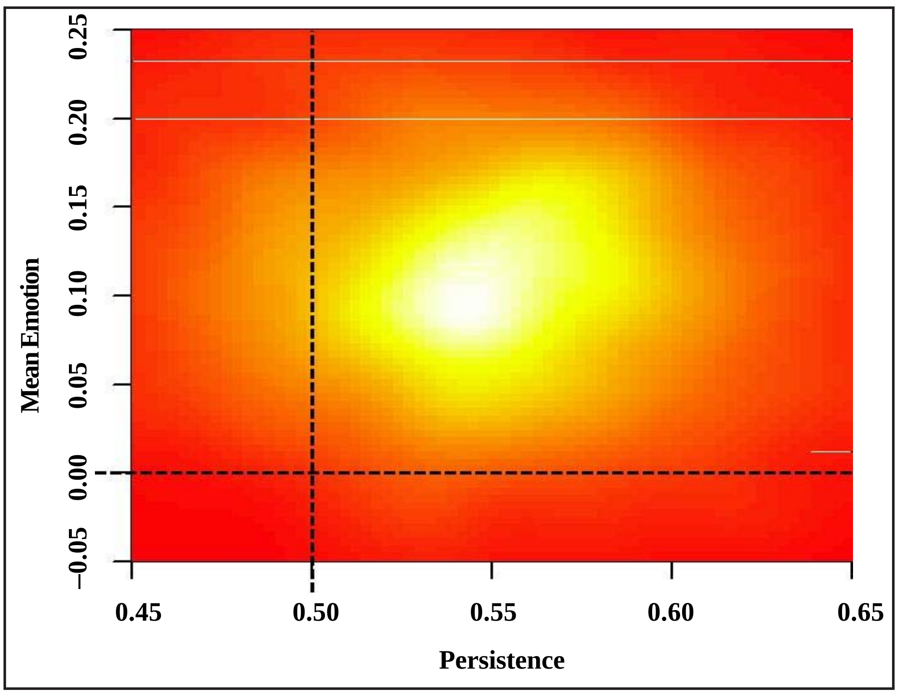

Figure 3. Kernel density plot of the distribution of individual persistences and mean emotional expression, for all users with more than 100 messages in the observed period [7]

4.3.3 Brownian agents model

While a persistence pattern for an individual user can be easily modeled with a biased random walk, the emergence of such collective persistence does not trivially follow from individual emotional expression. If we design a model which only ensures persistence in the behavior of an individual, the combination of expressions of many agents would show no persistence at the group level. Our aim is to provide realistic emotion dynamics, in which collective persistence appears in a discussion with many agents, which we reproduce with our Brownian agents model.

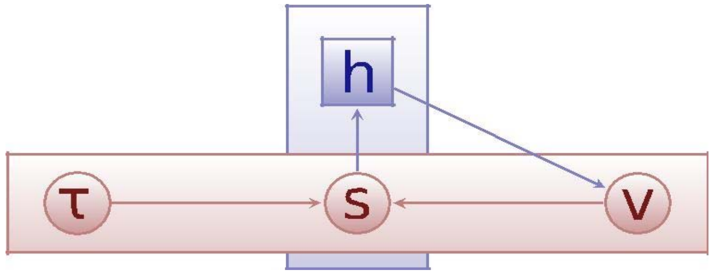

Figure 4. Schema of the Brownian agents model for IRC discussions (figure from [7])

The agent dynamics of this model is based on a combination of the empirical activity patterns mentioned above, where the time between the messages of an agent is given by *s*. These time intervals follow the distribution shown in Figure 2, and are a data-driven approximation for the dynamics of arousal, i.e., the degree activity induced by an emotional state. Figure 4 shows a schema of the design of this model, in which the horizontal layer represents the agent, and the vertical layer the communication medium, which in this case is the group discussion. Agents in this model have an externally observable variable *s*, which corresponds to the messages posted by the agent in the collective discussion. This variable of expression is activated according to τ, and its value is given by the internal valence of the agent *v*.

The communication in the group discussion is modeled through an information field *h*, which aggregates the emotional expression of all the agents. This field influences the dynamics of individual valences, creating a herding effect that reproduces collective persistence from the interaction of many individuals. Simulations of this model show how mean emotional expression and persistence depend on the parameter values [7], allowing us to simulate discussions that reproduce the observed group behavior. In terms of individual dynamics, the emotional profile of an agent can be sampled from the distribution shown in Figure 3, resulting in a data-driven simulation with corresponding parameter values in a way that provides the desired persistence and mean emotional expression.

This data-driven simulation using Brownian agents provides an account of changes in internal emotions due to perception of online content. These dynamics are integrated within the wider context of the real-time simulation of specific groups of agents for IABs as explained below, in Section 4.4, and further in the model definition, in particular the explanation of updates to agent states with Equation 4.

4.3.4 Model extensions

The Brownian agents model outlined here is a first approximation to the dynamics of emotions in online communities, which can be improved and extended with additional features within the same modelling framework [37]. The assumptions followed by models like the one explained above are currently being tested in experimental setups, which already revealed the patterns of influence of online interaction in internal emotions [17, 19, 8].

In a similar manner as the application shown here, a model within this framework is also used for the real-time simulation of emotional reactions in virtual humans [1, 12]. Furthermore, models within this framework can be improved with further results on emotional interaction in other online communities. For example, clustering measures from blogs and fora[7] [4] can provide empirical estimations of the conditional probabilities of emotional expression given previous messages. This extension has the added value of the analysis of the ending of forum discussions, which is not easy to analyze from realtime interaction like in the case of IRC channels commented above. This way, entropy measures and analysis of emotional content at the end of the discussion can be used to extend our Brownian agents model, allowing the dialog system to enhance discussion length and information exchange.

In the Brownian agents model shown here, interaction takes place in a publicly accessible discussion in which messages are not directed to individual users. Some of the questions listed in Section 4.2 aim at driving IABs in a way such that they can interact with individual conversation participants, by previous analysis of their position and influence in the overall discussion. Some

[7]Analysed data-set included 4 million post acquired from Blogs, Digg and BBC forums.

models within this framework include a network component that precisely deals with this kind of user heterogeneity [22, 47]. In real-time interaction, the network mapping approach [10] analysis[8] accounts for the properties of activity patterns and underlying network topologies characteristic for various types of users, including those identified as important/ influential in a given online interaction environment. In IABs, the spanning trees analysis can be specifically applied to analyze: i) user's activity, i.e.: by the creation and analysis of evolution of the network links, e.g., positive, negative, and ii.) users collective behaviour patterns. As demonstrated in high-resolution analysis of user-to-user communication in IRC channels, only certain links survive over one day period and support a particular type of network structure. Based on this observation, the presented system realizations and application scenarios presented in sections 5.1, 5.2 are primarily targeted at serving on-demand information requests of ecommunities or individuals, i.e., establishing a relatively short-time direct communication links. As experimental evidence demonstrates (see section 3), such direct, limited in time interactions with users, also contribute to an overall higher level of the perceived realism, dialog coherence, the feeling of an emotional connection and chatting enjoyment. In practical application and deployment scenarios, this often translates to a higher acceptance rate of interactive systems in online communities.

Overall, in the case of online communication channels such as IRC, an IAB can use statistics of emotions in the dialogue as a guiding factor for decision making. The insertion of objective comments or of equalising comments can potentially be used to further different goals regarding the wanted discussion length, i.e. either extending it or ending it earlier. By using the modelling framework for collective emotions, our Brownian agentsmodel does not simply provide realistic time behavior and emotional persistence, but allows the extension of our IABs to include present and future results on user heterogeneity, networked interactions, real-time influences, and information exchanges.

4.4 IAB - Modelling Individuals and Groups

Based on data on previous or the recent part of current interactions with a certain group (e.g., a chat room or a discussion channel), the agent control architecture of the IABs uses an online simulation model, *CybABMod* - Cyberemotions Agent-Based Modelling module, parameterised by the population and the history of the current channel, to derive particular models for the individuals it interacts with as well for the group as a whole. The output of such a simulation is a very short-term prediction, with a necessarily modest precision, of suitable candidates for interaction.

On the individual level, this model corresponds to the inference of specific "*personalities*" or personality types. These personalities are characterised by a collection of decision rules that abstract from previous interactions for that individual. A default personality is assigned to newcomers to a channel based on average behaviour of the channel so far. The simulation is updated online based on the tracked history and provides both short-term predictions as well as global attributes based on the theory input described above.

4.4.1 Representation of Networks and Interactions

A prerequisite to use modelling and simulation as part of the online decision structure, i.e. while interacting, is a suitable and flexible representation of interactions with the specific group that the system faces. In order to provide for that, we developed online data structures using the common terminology introduced by [15] layered on top of the HDF5[9] disk and memory data format [45]. The latter provides a suitable framework for both logging and analysis of chat-specific data as well as for configuration and initialization of online simulation at runtime, both for several networks concurrently.

4.4.2 Varying Degrees of Affective Capabilities

The baseline for the simulation of communicating agents or nodes uses stochastic modelling. One of the goals of this approach is to iteratively enhance the operationalisation of appraisal processes as described in theories of emotion [5, 6]. The minimum requirements for the modelling of appraisal processes in our nodes are representations of an agent's concerns or desires, including standards about praise- or blameworthy behaviour, as well as preferences for certain types of objects or situations. Further, a method for evaluating changes in an agent's environment based on these conditions is needed. For the purpose of e-communities, the changes to be evaluated encompass the posted messages and their content as far as it is modelled, but also the perceived entrance or exit of a participant in a discussion thread.

The modelling of a complete affective architecture is not the goal for these simulations. However, the introduction of specific *surface concerns*, i.e., concerns related to actual message exchanges as far as they can be observed, and a suitable approximation

[8] Analysis conducted on extensive data-sets from Ubuntu IRC channels: http://irclogs.ubuntu.com/

[9] http://www.hdfgroup.org/HDF5

of an agent's evaluation processes can be used to account for observed behaviour in e-communities as described in the following section.

4.5 Agent Modelling

Agents usually communicate to achieve specific immediate goals.Without semantic processing of utterances, however, we cannot explicitly relate actions to goals for individual agents. In our model, proxies for goals and motivations are derived from the annotations of activities of an agent inside the environment. We assume that the development of an agent is influenced by the emotional value of actions of selected other agents, reflected in the use of specific previous interactions as basis for deciding on agent actions. Our model combines the dynamics of core affect of the modelling framework for collective emotions [37], with the phenomenological theory of *appraisal* and *coping strategies*, which are conducive to cognitive modelling approaches at different levels of complexity [32, 14, 29] and allow for the application to IABs. Appraisal and coping are terms introduced in cognitive appraisal theories of emotion. In our design, these two concepts relate expectations and perception, updating internal states based on affective relevance of external events, driving decisions for sending events based on detected relevance [30, 31]. A typical definition of emotions in this context is:

> episodes of massive, synchronized recruitment of mental and somatic resources allowing to adapt or cope with a stimulus event subjectively appraised as being highly pertinent to the needs, goals and values of the individuals [35]

We represent emotional events using a two-dimensional model of *valence* and *arousal*. Note that this is a compromise motivatedmainly by available data annotation tools rather than a particular fit for modelling the particular domain. Even for a representation of emotion in only two dimensions, the processes of appraisal and coping still provide a framework for informing the state update of agents. Arousal, in this context, refers to user effort in expressing reactions in the online environment, while valence represents the positive or negative component of an emotion. For simplicity and again due to the availability of annotation tools, valence is represented as a single positivenegative polarity.

According to appraisal theories, emotions are elicited by a subject's evaluations of events or situations. Since the earliest introduction of appraisal theories in [2], many variants have been proposed, e.g. [33, 35]. Common to different appraisal theories is an account of how different affective responses of individuals can be elicited by the same stimulus [21], a prerequisite for the purpose of modelling a population of heterogeneous agents.

4.5.1 Model Definition

In our model, an agent can send a message with 3 parameters: receiver, valence, and arousal. The receiver of a message is optional to allow messages directed at all agents in a channel. Valence and arousal describe the affective content of a message, as far as that is possible independently of the receiver of the message and of its cause which could be an external event or an event in the channel. Thus, agents' external actions can be defined formally as the following tuple:

$$\begin{aligned} &A = \{\delta, a', v'\} \\ &\delta \in Agents \cup \{null\}, \\ &a' \in [-5...5] \text{ and } a' \in N, \\ &v' \in [-5...5] \text{ and } v' \in N \end{aligned} \tag{1}$$

with δ defining the destination, i.e. the receiver of a message (null for channel messages), a' defining the arousal value *expressed* through a message, and v' defining the valence value expressed through the message. The environment for all agents, E, is as an ordered history of all agents' actions, e_i, i.e. message events:

$$E = e_0, e_1, ..., e_n \quad e_i = \{T_i, \delta_i, A_i\}, \tag{2}$$

with T_i, a timestamp of the external action, i, its author and A_i, the external action expressed by this agent at that time. The index i ranges from 0 to n, the number of actions seen so far. A run of an agent in an environment is thus a sequence of self-dependent pairs of environment states (e_i) and agent's actions (A_i):

$$run : e_0 A_0, e_1 A_1, e_2 A_1, ... \quad (3)$$

To model the effect of this communication history on agent behaviour, we use an reactive stateful agent. Its action-selection function action maps internal states *I* to *actions*. An additional function next maps an internal state and a percept *Per* to a new internal state:

$$action : I \mapsto A, \quad next : IxPer \mapsto I \quad (4)$$

The internal state of our agent consists of a current emotional state, ε, as well as a structure representing the agent's specific personality, $\prod$.

$$I = \{\epsilon, \prod\}, \epsilon \in [-5...5] \text{ and } \epsilon \in R \quad (5)$$

When driven by a simulation of the Brownian agents model explained in Section 4.3.3, the emotional state ϵ of the IAB is given by a rescaling of the internal state of the Brownian agent ν. This way, the perception rule *next* is able to reproduce the patterns of individual and collective persistence found in the empirical analysis explained above.

The other part of the state of an agent is its personality, $\prod$, consisting of a set of rules, r_i. A rule is an n-tuple of information abstracted from trigger events that previously elicited a type of reaction in the history of the agent:

$$\prod = [r_0, r_0, ..., r_n] \quad (6)$$
$$r_i = \{T_t, \epsilon_t, \delta_t, a'_t, v'_t, T_r, \epsilon_r, a'_r, v'_r\}$$

T_t and T_r, are exact timestamps of the occurrence of a specific trigger and the corresponding reaction. The trigger parameters T_t, ϵ_t, δ_t, a'_t, v'_t represent a class of situations that have occurred. The reaction parameters T_r, ϵ_r, a'_r, v'_r record the specific reaction triggered, its reaction time, destination, arousal, and valence. This personality structure retains a selection of, potentially abstracted, cases available for future decisions similar to case-based reasoning. Rules are derived from previous experience in the reference data similar to rule induction in machine learning applications.

4.5.2 Agent Initialization and Update

During initialization, the personality structure of an agent is constructed based on the available data for the history of a chat community. However, not all agents that will be encountered later appear in the data available during initialization. During online simulation, a model frequently encounters new agents. One required feature of the presented model is, therefore, to be able to readily account for new agents during the model run.

In order to model participants of an online discussion in real time, the agent model needs to be updated continuously. Both initialization training data, or recent changes in the channel, can indicate that an agent reacts with a specific action to a trigger. As a consequence, a rule *rx* is created as defined above as a new candidate for the agent's personality structure $\prod$. If the structure already contains a rule *ry* which is sufficiently similar to *rx*, we increase a count for that specific rule. Two rules are considered to be sufficiently similar when parts of the rule-tuples correspond exactly and the timing of the reaction is similar:

$$\mapsto \{\epsilon_t, \delta_t, a_t, \delta_r, a_r, v_r\} rx = \{\epsilon_t, \delta_t, a_t, \delta_r, a_r, v_r\} ry \quad (7)$$
$$and$$
$$||(T_r)_{rx} - (T_t)_{rx}| - |(T_r)_{ry} - (T_t)_{ry}|| < \epsilon_{TIME} \quad (8)$$

where ϵ_{TIME} is a number of seconds, e.g. 10, 60, 300, etc. If no such rule *ry* is found the new rule *rx* is added.

An important aspect of this model is the consideration of the agent's current emotional state for rule similarity and action selection. This accounts for the individual difference between people in different emotional states and is directly derived from their specific communication history. Behaviour in a variety of situations can be used to approximate an agent's coping strategy for situations characterised by the emotional state, motivating the use of the term personality.

In the version of the model used for online decision making, only events that directly target an agent as indicated by the receiver are considered. This has the beneficial side-effect of reducing the runtime complexity of the model, allowing it to be used in real time for online communities with many participants. Whenever an event causes an update to the personality structure of an agent, i.e. when a sufficiently similar rule was already present, its action module uses this information to perform an action thereby leading to a short-term prediction.

These kind of short-term predictions are only useful in small timewindows, but for those they can provide a conversational system with an overall characterisation of the level and emotional charge of activity to be expected in the channel. They further provide a hint as to which users might be active in the near future.

5. Realization of Interactive Affective Bots for Multiple User Environments

Below, we introduce two realisations of IABs that integrate modelling of individuals and groups as part of their decision mechanism.

5.1 Affective Interaction Analyser

In the default settings for mult-user environments, such as e.g. IRC or Reddit[10], the Affective Interaction Analyser (AIA) focuses on the analysis of the interaction patterns, affective content of the exchanged textual messages between the discussion participants and the tracking of group-level attributes characteristic of the affective group dynamic (see section 4.3). The content of the collected messages feeds into the tracking of the current observed affective state of a group, is part of the input to the CybABMod simulation, and thus influences the predictions of the possible outcomes of ongoing interactions. Similarly, like in previous realizations of the system, the AIA's architecture includes three layers: perception, control and communication. The functionality of the layers was however extended to allow for simultaneous perception of users' actions in a multiple users environment. This functionality provides a base, both for the analysis of individual users activities and for modelling of the whole group. Based on the input from the environment (e.g. system messages for an IRC channel as well as the formatting of messages), the perception layer identifies users' IDs and the range of actions typically performed in an interaction environment, e.g., joining and leaving a channel, changing a nick-name, posting a link or utterance. This realization of the system, is the least active in terms of interactions with casual users. In these settings, the bot's interaction capabilities are typically limited to infrequent messages that can be provided to selected participants, in particular to the channel operators in the case of IRC channels or the subreddit moderators in the case of Reddit, e.g., on demand or based on a set interval or threshold set for the observed affective and interactive states of a group.

5.2 Affective Supporter and Content Contributor

Depending on the foreseen experimental settings and tasks for IAB, the activity level settings for the bots in an environment such as e.g. IRC or Reddit, can be set between the two above presented conditions "*Dialog Participant*" (highest activity level) and "*Affective Interaction Analyser*" (lowest activity level), enabling the Affective Supporter and Content Contributor (ASCC) to participate to a moderate extent in an ongoing discussion by providing both new content, related to the discussed topic (e.g., link to a relevant website) or the results of affective group dynamic analysis and real-time simulations. This realization of the system, relies on the architecture presented above, i.e., "*Affective Interaction Analyser*", extended to provide additional interactive capabilities targeted to the whole group such as posting comments (i.e., affect analysis based, relevant to the observed affective states of the group) or website links relevant to the ongoing discussion (i.e., content related [38]). In the Affective Supporter and Content Contributor scenario, the IAB combines the ability to directly respond to a range of events, such as:

- changes in the environment, e.g., a user joins/leaves the channel, posts a link or comment, (updating the interaction and group status, based on the set interval or threshold - sending messages to channel operator), changes in the affective state of the group, e.g., sudden decrease of the valence, increase of sentiment polarity in the posts exchanged between users,

- changes in the activity of the group. For example, the detection of a decrease of the participants activity might lead to emitting a message or posting a new link, or comment respectively, to a single user as selected by the simulation model. Further, in this scenario the interactive bot can also provide information about an event from the "*offline*" world related to the discussed topics, or emit questions aiming to stimulate the interactions,

[10] http://www.reddit.com

- responding to utterances or comments emitted directly to the IAB by users.

6. Conclusions and Discussion

To summarise, in the presented system applications, the system-user communication is text-based, real-time and oriented at the detection and acquisition of users affective states. Communication with the system is not limited to a specific domain, topic, or one particular ICT-mediated community. Naturally, interactive systems like these, are strongly limited in the sense that they cannot match the conversational abilities of a human, in particular in interaction scenarios that include long-term communication, and further which need to combine open- and closed-domain dialog and discourse processing. However, as the experimental evidence presented in section 3 demonstrates, in 1-on-1 communication settings and relatively short communication scenarios, i.e., chat sessions that are a few minutes long, the systems could match the WOZ results in terms of dialog realism, chatting enjoyment and the ability to establish an emotional connection with users. Further, the analysis of activity patterns and affective dimensions of users' communication in multi-user environments presented in section 4.3 showed that the majority of links are established only temporarily and primarly used to exchange relevant information, to share or respond to a sentiment expressed. These results support the proposed application scenarios where the systems establish communication links in a way similar to their human counterparts: on demand basis, and for a limited time-span. Consequently, the IABs communicate directly with users in situations where high confidence scores for a potential contribution's relevance, i.e. added informational or affective value - *contribution value*, can be foreseen. These estimates are based on the outcomes of the simulation of the reception of a specific content by a particular individual or a group. Additional *action costs* are associated with interaction scenarios where posts need to be emitted to a large number of participants or to the whole e-community.

Related to the classical Turing Test setup [46], the focus on other aspects than discussion content is sometimes used to deal with system confusion, e.g., system inability to respond based on analysis of semantic content, expected states in a dialog, pragmatic context or a simple detection of keywords. In the case of the presented systems, the focus on affective content is deliberate. This approach, i.e., generation of the selected system responses based on the detected affective states of individuals or groups can be seen as complementary to continuous extending and updating of knowledge bases necessary to respond to open-domain inputs. In a range of application scenarios, a pre-requisite for a successful application of such interactive systems could be the ability to adjust (or at least foresee the outcomes of an intentional violation of) one's communication behavior or affective stance according to: the overall mood detected in a group; individuals' preferences to various entities or fellow participants; the established or evolving "*social norms*"; or dynamic changes in a hierarchy of interaction patterns of users. Social intelligence also plays a role in a 1-on-1 interaction scenario, and as such is relevant for the Turing Test. However, the classical Turing Test was neither the primary goal of the Affect Listener systems nor required for them to fulfill their purpose.While the interaction is, as mentioned above, unrestricted, the domain is constrained in so far as the system concerns itself mainly with the emotional states of individual participants as well as the dynamics of collective emotions and employs suitable strategies to keep the conversation or interaction between members going.

The setups in which an agent or group of agents interacts and cooperates with a large number of users provides new challenges but also offers new opportunities for the evolving intelligence and adaptability of the artificial systems. As demonstrated in nature, when the communities begin to evolve from a scenario of low cooperation, towards a more cooperative scenario, the more advanced solutions for intelligence are obtained. This is particularly relevant for the evolution of social intelligence: interactions that require indirect reciprocity, are cognitively demanding, or where individuals need to constantly monitor the social constellation of a group. Clearly, all of these factors - to a different degree - are present in different online communities, and need to be addressed to a possibly large extent, when envisaging new supportive roles for artificial agents in such multi-user settings. Such interaction settings also influenced the evolution of human language [24].

In this paper, we presented the design choices for using agentbased simulation as part of the decision mechanism of Affect Listeners. The use of the simulation as decision support for interactive affective systems adds different requirements including real-time and online use. Both of these connections contribute to the design of the simulation. The ALs are interactive affective systems that are also used for acquiring data, and for studying online interaction. The initial realisations of the systems were applied in dyadic experimental settings, demonstrating the ability to generate an enjoyable and realistic dialog on par with WOZ settings. Further, using the AL, we studied the role of affective profiles in dyadic settings. For future work, we are interested in measuring the effect of the interactions with the systems on participants' emotional (physiological) responses and to relate and align those with the textual expressions of users' affective states observable during interaction.

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