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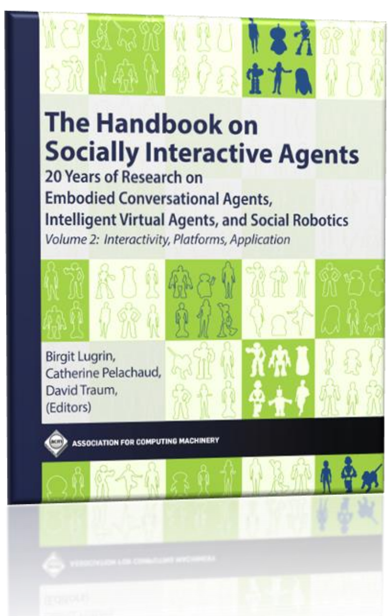

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17 Multiparty Interaction Between Humans and Socially Interactive Agents

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17.1 Motivation

While most research has focused on one-on-one interactions, Socially Interactive Agents (SIAs) for multiparty interaction have received increasingly more attention in the past years for a number of reasons. First, multiparty social interactions are often more unstructured but also more likely to resemble real-world situations. As these agents move from lab environments to the real world (e.g., museums, hospitals or classrooms), it is important that they can handle the different types of social situations that may arise. Second, human social behavior is largely dependent on social context, for example, the way we behave alone is different from how we behave in a group [Zajonc 1965]. For this reason, we cannot directly assume that empirical findings, computational models, etc. from one-to-one interactions between users and SIAs will hold in a multiparty setting.

When compared to one-on-one interactions, multiparty settings pose additional challenges for humans. Thus, it is no surprise that they can also be more challenging for SIAs. The core capabilities in this domain are no less social than at the individual level, but typically relate to space management, formation control and navigation. Additionally, questions such as how the agent behavior and appearance can positively affect group dynamics (e.g. collaboration or teamwork), as well as users' subjective experience (e.g. perceived presence or trust) are relevant to explore in a multiparty context. Therefore, robust multiparty interactions involve a large set of competencies to some degree, combining the challenges from one-on-one interactions while also raising new challenges. For example, conversational management can become more difficult with more participants in aspects such as turn-taking, verbal and non-verbal communication. When considering embodied agents, how should these agents position and orient themselves within the group such that they can equally participate in the interaction? Finally, when it comes to perception, so far, little is known about how perception models perform when they are tested in a group size different than the one they were trained on. However, this feature is critical for some perception problems, i.e., the way in which an agent should interpret a user glancing to the side is different if that user is alone or if the user is in a group.

One can consider interactions between humans and SIAs to take place at three levels: crowd, group, and individual levels [Panzoli et al. 2010]. Research to date has been focused in separate strands on the crowd and individual levels, but modeling multiparty interactions at the level of small groups (the main focus of this chapter), has not received as much attention in the literature; yet, it is crucial for more natural interactions in many real-world situations.

Another important differentiation relates to whether SIAs are static or mobile within the environment. The former case relates to situated social gatherings that take place in a specific location, for example in the case of free-standing conversational groups, in contrast to those situations in which participants move together through an environment toward a shared destination. Our focus in this chapter will primarily be on the former case, in which the group is in a static position within the environment. It should be noted that, even in cases in which the group might be considered to be static in its locale, individual agents may still have some mobility. This may be due, for example, to individuals changing their positioning within a formation during the course of an interaction to accommodate newcomers or re-form due to a departure of a group member.

This chapter surveys recent work on multiparty SIAs, focusing on small group interactions or social gatherings (with multiple humans and/or multiple agents). We begin by introducing models and approaches from other disciplines and then summarize the recent advances in multiparty interaction with both Intelligent Virtual Agents (IVAs) and Social Robots (SRs). We then summarize some of the main similarities and differences between IVAs and SRs in multiparty interaction, in an attempt to establish synergies between the two communities. We conclude by discussing current challenges and future research directions.

17.2 Models and Approaches

This section serves as an overview on models, approaches and background knowledge from other disciplines that are commonly used in research concerning multiparty SIAs.

Social Gatherings

In social psychology, *gatherings* correspond to a set of individuals who are in one another's immediate presence [Goffman 1963]. Unfocused gatherings are typically associated with mere co-presence, such as pedestrians on a street or strangers waiting for a bus. Focused gatherings are instead characterized by individuals coming together to sustain one focus of attention.

According to Kendon [1988], there are two main types of focused gatherings. If there is a joint responsibility between the people in a gathering to cooperate to sustain a focus of attention, the interaction is considered a *jointly focused gathering*. Examples include social conversations, ping-pong games, dancing partners, and groups of workers cooperating to solve a task that requires sustained attention. When there is no need for shared cooperation to sustain the focus of attention, the interaction is rather considered a *common focused gathering*. For instance, common focused gatherings include a platoon on a parade or pupils paying attention to what a teacher says in a classroom.

Information is given voluntarily during gatherings, e.g., through what people say. In addition, information is given off whether the interactants choose to provide it or not. As Kendon [1988] described, this is an inevitable and unavoidable product of people's presence and of their actions. For example, groups of people might provide additional information through their gaze or spatial patterns of behavior. While the latter aspects may seem unimportant in comparison to the information that is provided voluntarily, they play a key role in structuring social encounters.

Situated human conversations have traditionally been considered the most common type of jointly focused gatherings [Kendon 1990]. The members of these gatherings converse in one another's immediate presence. They work cooperatively to sustain their focus of cognitive and visual attention, pursuing a common line of concern. The cooperative nature of conversations means that they often end when a participant has the turn to speak but, for some reason, he or she does not do it.

Groups and Teams

An important distinction is often made between gatherings involving groups of agents and teams [André et al. 2020]. Groups correspond to agents that are aware of having a shared identity. Meanwhile, teams are more specific. They are groups in which the agents have a shared goal or task [Groom and Nass 2007]. Team members collaborate and support each other to accomplish their joint goal(s). Worth noting, the success of teams is not a given. Team characteristics such as member's perceived inclusion [Jansen et al. 2014] and psychological safety [Edmondson 1999] are typically associated with effective teams. Readers interested in a broader discussion of team performance from an organizational psychology perspective are encouraged to refer to [Guzzo et al. 1995].

Proxemics

An important aspect of social gatherings pertains to people's use of physical space, or *proxemics* as coined by Hall [1966]. Hall described four distance zones typically used by people during interactions. These zones correspond to the intimate, personal, social, and public distances that people tend to keep from each other based on their emotional state and type of social engagement. The intimate distance is short, affording physical interaction. Personal distances are often kept by friends or family when conversing, whereas social distances are more common for acquaintances during situated social gatherings. Finally, the public distance is well outside an individual's circle of personal involvement, typically emerging during public addresses. Several factors are known to influence human proxemics,

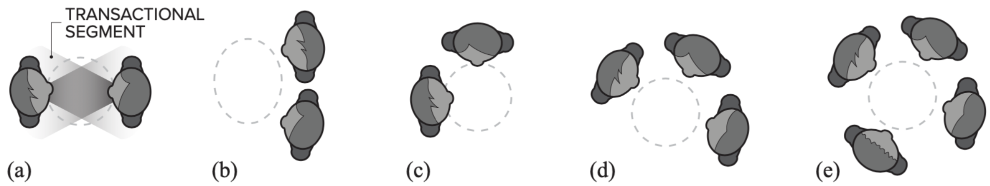

Figure 17.1 Spatial arrangements typical of F-formations: (a) face-to-face arrangement; (b) side-by-side arrangement; (c) L-shaped arrangement; (d) semicircular arrangement; (e) circular arrangement. Dashed areas represent o-spaces. [Adapted from Vázquez et al. 2016].

including lighting [Adams and Zuckerman 1991], cultural factors like social norms, peoples' familiarity with one another, and to what degree people interact together [Argyle 2013].

Face-Formations in Social Conversations

During conversations among free-standing people, the participants position themselves to create a sort of "no-man's land", maintaining a separate world from their surrounding [Kendon 1990]. The result is a distinct spatial organization, typically known as a face formation or *F-formation* in short within social psychology. F-formations maximize the opportunity of the interactants to monitor one another during conversations. They also help maintain groups as spatially distinct units from other nearby focused gatherings.

Kendon [1990] described the emergence of F-formations and their structure based on observations of social events. F-formations begin when the members of a group position themselves such that their *transactional segments* intersect. These segments correspond to the physical space in front of each person. They correspond to the space into which individuals look and speak, or into which they reach to handle objects relevant for their current task. People will work to maintain their transactional segment free of intrusions for as long as they are engaged in an activity that requires it.

The physical area where the transactional segments of the members of a conversation intersect is the *o-space* of the corresponding F-formation. As shown in Figure 17.1, the o-space is in-between individuals in a group, whether they are standing in a face-to-face arrangement or in semicircular or circular formation.

The spatial organization of the participants of a gathering often reveals transitions between social conversations and other types of interactions. For example, F-formations often transform into a less uniform spatial arrangement when a conversation shifts into a common focus encounter [Kendon 1990, Marshall et al. 2011]. When the focus of attention becomes a particular person, a separation between this interactant and the rest of the group is often observed due to a difference in social status or role.

Other Group Phenomena

F-formations are one type of group phenomena that emerges during social gatherings, but other important phenomena relate to group social influence. For example, *conformity* [Crutchfield 1955] concerns agreement to the majority position within a group. Kelman [1958] distinguished between three processes that result in group influence: *compliance* to fit in within a group; *identification* which results in compliance to establish or maintain a desired relationship within a group; and *internalization* which occurs when the adopted ideas or behavior is intrinsically rewarding.

Other related group phenomena in multiparty human interactions include *diffusion of responsibility* [Darley and Latané 1968] and *group polarization* [Myers and Lamm 1976]. The former phenomenon is said to emerge when the likelihood of people taking the responsibility for action or inaction is reduced in the presence of others. The latter phenomenon results in groups making more extreme decisions than their individuals would in isolation.

Relevant concepts frequently used in the social sciences to study group dynamics [Abrams and Rosenthal-von der Pütten 2020] comprise: *Ingroup identification*, the individuals' perception of themselves as member of the group [Ashmore et al. 2004, Leach et al. 2008]; *cohesion*, the inside perspective on the forces that keeps the group as a group [Dion 2000]; and *entitativity*, the outside perception of the groupness of a social group [Campbell 1958].

A phenomenon that not necessarily arises from but might influence small group interactions is *ingroup-favoritism*. Ingroup-favoritism has been phrased by the findings that people tend to act more favorably toward ingroup members than toward outgroup members [Brewer 1979, Tajfel et al. 1971].

17.3 Advances in Multiparty Interaction

The development and evaluation of SRs that can interact with groups of people has been explored in several domains. In the following sections, we review different aspects of multiparty interactions and the respective capabilities of SIAs.

17.3.1 Evaluating and Understanding Groups

Group dynamics encapsulate the influential actions, processes and changes that are observable within and between groups. Group dynamics change the individuals in the groups in which they occur and, potentially, even their society [Forsyth 2018]. This makes the study of groups and group dynamics interesting for creating SIAs.

The next sections discuss research on multiparty interaction regarding the believability of SIAs in group settings, users' attitudes toward these agents, and spatial group behavior. We also discuss prior efforts aimed at understanding human-agent group dynamics.

Measuring Believability

Human perception studies have been used to evaluate the behavior of small groups of virtual characters, often focusing on human sensitivities to different behaviors and their impact on believability or perceived naturalness of the group. These include studies investigating whether people are more sensitive to similar appearances or motions in a group of characters when perceiving their variation [McDonnell et al. 2008], the number of agents per group and distribution of groups that appear to be the most realistic in crowd situations [Peters and Ennis 2009] and the degree to which people are able to see groups in a crowd as the camera viewpoint and crowd density are varied [Yang et al. 2018].

McDonnell et al. [2009] investigated human sensitivity to the coordination and timing of conversational body language in small groups of virtual characters, and concluded that participants are sensitive to desynchronizations in the turn-taking behavior across group members. Ennis et al. [2010] investigated sensitivities to desynchronizations of body motions, gestures and voices in small groups and found that viewers were most sensitive to desynchronizations of full-body motions.

Measuring Attitudes

Different behaviors employed in SIAs interacting in multiparty environments have been shown to affect the perception on themselves. In the following paragraphs, we review studies that evaluate attitudes toward SIAs.

The study by Cafaro et al. [2016] investigated the interpersonal attitudes (friendly versus unfriendly) of agents within a small group and toward an approaching avatar and found that the interpersonal attitude of the group had an impact on the proxemics behavior of the avatar. Further, it was found that the attitude of the group toward the approaching avatar had a major impact on social presence evaluations. Pereira et al. [2014] created a case study in which a social robot plays the Risk board game against three human players in order to investigate if the agent was perceived to be socially present.

Fraune et al. [2015a] examined how humans respond to different numbers of robots (one versus three) with different social capabilities (social versus non-social) in a naturalistic scenario of robots acting as trash collectors. When robots were acting in a sociable manner toward another robot, they were perceived as more anthropomorphic. If the same robots were acting sociably toward humans, positive attitudes and emotions, the willingness to interact and encountered physical proximity were improved [Fraune et al. 2020]. In a different multirobot environment, Tan et al. [2019] found that the sociability of a pure functional robot can be increased through witnessing social robot-robot interaction.

Humans but also robots can be seen as members of an ingroup or outgroup [Kuchenbrandt et al. 2011]. The introduction of a robot as ingroup versus outgroup was found to increase the positive perception of the robot [Kuchenbrandt et al. 2013] and social categorization has been found to play an important role when perceiving the robot as an ingroup or outgroup [Eyssel and Kuchenbrandt 2012]. When humans are paired with robots in a competitive game humans perceive their own team as an ingroup and the other human-robot team as outgroup. Allocating painful noise bursts to ingroup and outgroup humans and robots revealed that humans develop ingroup favoritism for robots over humans as they prefer ingroup robots over outgroup humans [Fraune et al. 2017b].

Cultural aspects as well as gender and personality are important components in multiparty interactions involving SIAs. Endrass et al. [2011] focused on how human observers perceive culture-related differences for groups of two virtual agents engaged in small talk i.e. informal discourse behaviors. The results from a study are used to inform a model for the automatic generation of culture-specific small talk dialogs for virtual agents. Mascarenhas et al. [2016] found participants prefer those group of IVAs that display the same cultural bias (individualistic versus collectivistic) as present in their own culture. Damian et al. [2011] developed a software framework that allows IVAs to display differences in personality and gender which also influence group formations.

In general, the results from these studies are intended to inform the creation of more believable and effective group behavior generation models [Huerre et al. 2010].

With an increasing number of SRs present in everyday and work environments, robots are to be expected to work in teams with humans. Specifically when humans and robots partner in teams against another human-robot team, aspects of the robot behavior have shown to be influential on the group. When robots show different orientation goals (competitive versus cooperative), interaction patterns differ in terms of socio-emotional support and gaze behaviors [Oliveira et al. 2018]. Further, expressing different levels of warmth and comfort has shown to influence feelings, perceptions and future intent to work with the robot [Oliveira et al. 2019]. In addition, a robot expressing group-based emotion in this kind of setting can lead to higher group identification, group trust and likeability of the robot [Alves-Oliveira et al. 2016, Correia et al. 2018]. As a different aspect of the human-robot partner interaction, Correia et al. [2016] found that previous encounters with the robot partner positively influence trust toward this robot over the course of a game. From a theoretical point of view, de Visser et al. [2019] propose a human-robot team trust model that builds upon relationship equity and aims to ensure longitudinal trust.

The appearance of robots and groups of robots has been found to have influence on the attitudes toward those. Influence on the perception of robot groups was found based on different robot types - mechanomorphic, zoomorphic, and antromorphic. An interaction between type and perception of groups versus individual robots was reported by Fraune et al. [2015b]. Further, entitative robot groups were perceived as more threatening than diverse groups [Fraune et al. 2017a] and a correlation between the perception of entitativity of the robot group and fear toward this group was found [Fraune et al. 2019b].

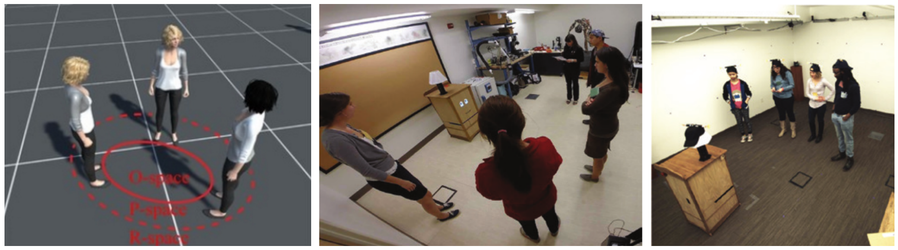

Figure 17.2 Spatial behaviors have been studied among SRs and IVAs. The left image shows IVAs positioned in formation accounting for social spaces with O-, P- and R-spaces illustrated [Adapted from Yang and Peters 2019c]. The other two pictures illustrate F-Formations with a furniture robot. The middle image shows the circular arrangement during a social role-playing game [Vázquez et al. 2015]; and the right image the circular arrangement during a brainstorming activity with the robot [Vázquez et al. 2017].

Spatial Behavior Understanding

Other studies have investigated group formations and behaviors taking place within the group. A study by Ennis and O'Sullivan [2012] indicated that participants were sensitive to the distance and orientation of individual agents in social formations.

The study by Carretero et al. [2014] explored the impact of task-irrelevant background expressions on the perception of emotional expressions of a small group of foreground characters and found that a consistent impact of task-irrelevant negatively valenced background stimuli on the perception of the emotions of the foreground task-relevant group of characters.

Palmberg et al. [2017] conducted a study investigating the impact of facial expressions and full body motions on the perception of intense positive and negative emotional expressions in a group of three virtual characters and found that the emotional valence of facial expressions had a stronger impact on the perception of emotions in the group than body motions.

Understanding spatial behavior has also become increasingly important in human-robot interaction. Several factors can influence the level of comfort that people have with robots and, thus, the distance that they like to maintain from them. For example, these factors include a robot's gaze [Mumm and Mutlu 2011, Ruhland et al. 2015] and personal experience with pets and robots [Takayama and Pantofaru 2009]. In regard to spatial behavior typical of conversations, several efforts have provided evidence of the emergence of F-Formations in HRI [Bohus et al. 2017, Huettenrauch et al. 2006, Vázquez et al. 2014, 2015, 2017]. The distancing between robots and group members during F-formations might be influenced by the specific embodiment of the robots, although more research is needed to systematically understand such potential effects. Figure 17.2 illustrates how humans build F-Formations when interacting with a robot and how virtual agents position themselves socially.

Interestingly, Kuzuoka et al. [2010] showed that a robot can influence the body orientation of a museum visitor by rotating its own body. This suggests that people may adapt to robots' spatial patterns of behavior in a similar manner as they adapt to human spatial behavior during situated conversations. Further, Yousuf et al. [2012] and Vroon et al. [2015] investigated suitable social positioning behaviors for mobile robots during social interactions.

Understanding Group Dynamics

A different set of works has investigated how SIA behavior affects the human group members or how groups of SIAs can affect human behavior.

How an SR could interact with groups of people in a museum or shopping mall was early investigated by Bennewitz et al. [2005] and Kanda et al. [2010]. Asking which kind of groups of people would interact with a robot in an open setting such as a shopping mall, Fraune et al. [2019a] found that highly cohesive groups engaged in longer conversations with the robot and acted more socially and positively toward the robot. Further, people who were by themselves unlikely to approach the robot were encouraged through the group and the group's norms to interact with the robot. When groups of people and robots interact in a prisoner's dilemma, it was shown that the number of people in the group significantly affected cooperative behavior [Chang et al. 2012]. In this experiment, those who interacted individually with the robot cooperated more with the robot than those interacting in pairs. However, the number of robots that pairs or individuals interacted with did not affect cooperation. When interacting with either one or three robots, individuals and groups, further, showed more competitive behavior when interacting with the same number of robots [Fraune et al. 2019b].

The influence of the group of robots that a human joins when making decisions was studied under the aspect of conformity and peer pressure. Where adults as opposed to children did not conform to a group of robots when the answer was unambiguous [Brandstetter et al. 2014, Vollmer et al. 2018], adults could be convinced by a group of robots if there was no objective correct answer [Salomons et al. 2018]. A further finding of this work indicates that the level of conformity depends on the level of trust toward the group of robots, here influenced by the correctness of the robots' decisions. Considering the aspect of cultural differences, Wang et al. [2010] have shown that the way a robot can influence group decisions can be depending on the cultural origin of the participants. Exploring conformity from a robot's perspective, Tokumaru [2019] investigated how conforming robots influence human decision-making. As one aspect of non-verbal behaviors, human-like gaze patterns directed toward two listeners during a story-telling task have been found to help story recall [Mutlu et al. 2006] and to increase the persuasive power of a robot [Ham et al. 2011].

Intentional group coordination is occurring when a group of humans joins in a cooperative group task such as dancing. One and two robots joining the coordinated group task have been shown to affect the group dynamics [Iqbal and Riek 2017b].

Addressing the question of team performance, backchanneling has been found to ease cognitive load and stress in a complex task [Jung et al. 2013]. With the goal of improving small-group decision-making meetings, Shamekhi and Bickmore [2019] investigated how a robot could act as a facilitator. Moving to education environments, Rosenberg-Kima et al. [2020] explored the potential of a robotic facilitator for small-group learning in higher education and compared it to teacher and tablet facilitation.

Like work teams, groups of family members have been studied. A robotic therapist has been shown to improve intimacy and positive affect between romantic couples [Utami and Bickmore 2019]. Short et al. [2017] explored how a socially assistive robot could support intergenerational family groups, i.e. older adults in these groups. In a different family setting, Gvirsman et al. [2020] explored how the triadic interaction between toddler, caregiver and robot can be beneficial for early second language learning.

By giving virtual agents the possibility to use different physical appearances, Reig et al. [2020] found that personalization could be exploited when interacting with multiple users by exploring the concept of *re-embodiment* and *co-embodiment*.

Influencing Group Dynamics

As different works discussed in the previous sections have also found effects on group dynamics, research interests have been targeted at robots and their behaviors that can positively influence the dynamics in a group of humans. This influence can be twofold and either impact how humans act among each other or toward the robot. The robot's efficacy has been discussed for different aspects of group processes. In the following, situations of conflict, inclusion, collaboration, robot abuse and conversation will be discussed with the approaches taken to improve these situations with the help of SIAs.

Different roles that an SR might take in a group set-up have been explored, and Engwall et al. [2020] discuss four roles that a robot could take in a triadic language café setting. To improve conversations and meetings, SRs have been employed as facilitators. With the goal of balancing participation, Matsuyama et al. [2015] proposed a facilitation model incorporating the robot as a fourth participant, and Shamekhi and Bickmore [2019] investigated how a meeting facilitator could in addition ensure an efficient meeting. With the same goal in mind, another work used a microphone-shaped robot - Micbot. Micbot was shown to be able to balance the engagement of a group of three and thereby achieve higher group performance [Tennent et al. 2019]. The robot could encourage passive members to participate more actively with non-verbal and indirect cues executing two distinct behaviors - *follow* and *encourage*. By employing a robotic object as a side-participant [Hoffman et al. 2015] in a debate, Rifinski et al. [2020] found that minimal movement implying gaze and leaning can improve the interaction and the interpersonal evaluation. In an application in a virtual city, balanced theory has been found to be applicable when a virtual agent mediated a conversation between two avatars and influenced the attitudes toward itself [Nakanishi et al. 2003].

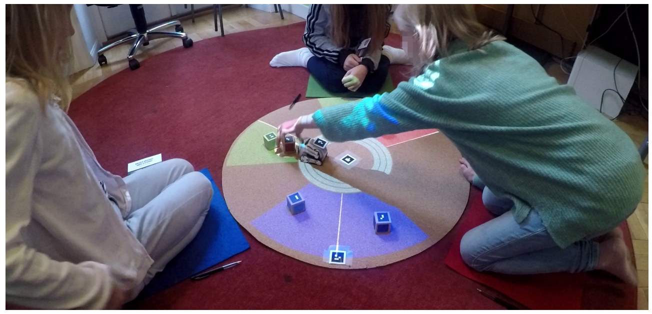

Figure 17.3 Different works investigated how a robot could influence the dynamics of a group, in this case, the robot Cozmo by Anki mediates an interaction among children and aims to foster collaboration and inclusion [Gillet and Leite 2020].

Taking a different role in the group setup, robots have been used as mediators in conflict situations. For example, a robot could promote more constructive conflict-solving behavior in cases of object possession conflicts among children [Shen et al. 2018]. When personal violations cause a group conflict, a robot acting as an emotional regulator was found to regulate and call attention to a conflict [Martelaro et al. 2015]. The role of IVAs for mediating conflict was explored in a debriefing scenario [Haring et al. 2019].

Moreover, different works have explored how to facilitate collaboration and group cohesiveness by comparing task-focused and group-focused robot behavior. Thereby, a robot that was employed in the role of moderator displaying performance reinforcing (task-focused) behavior increased group cohesiveness [Short and Mataric 2017]. The study indicates that the intuitively contradicting results are leveraged by the robot addressing participants more evenly when displaying task-focused behavior. To improve human-human collaboration among children, relation-reinforcing utterances have been found to enhance the perception of team performance [Strohkorb et al. 2016]. But neither task-reinforcing nor relation-reinforcing robot behavior was found to influence short-term group cohesiveness.

Addressing the problem of inclusion of an outgroup participant, Sebo et al. [2020] explored different strategies on how an SR could be employed to support the process of inclusion. To support the inclusion of children that newly arrived in a country, Gillet et al. [2020] developed a robot-mediated music-mixing activity that allows the robot to perceive group dynamics and act upon them. The music-mixing activity is shown in Figure 17.3.

As an important factor in groups, the level of trust in a mixed human-robot group has been found to be influenced by a robot verbally expressing vulnerability. This expressed vulnerability produced a ripple effect throughout the group which increased trust-related behaviors within the group [Strohkorb Sebo et al. 2018] and improved conversational dynamics [Traeger et al. 2020].

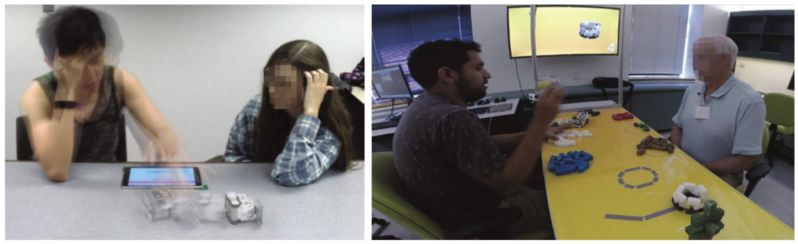

Figure 17.4 Two scenarios in which Cozmo robot(s) by Anki aim to influence a human bystander such that (s)he intervenes to stop robot abuse by a confederate. [Adapted from Connolly et al. 2020, Tan et al. 2018]

Work on conformity and group social influence has also inspired efforts on prompting human bystanders to intervene in robot abuse [Connolly et al. 2020, Tan et al. 2018]. This line of work has shown that the reactions of the abused robot can influence how much bystanders perceive adversarial actions toward robots as mistreatment. Further, it suggests that emotional group robot responses can increase bystander interventions in comparison to when they ignore the abuse. Figure 17.4 illustrates examples from this line of work.

17.3.2 Automatic Perception of Group Dynamics

For SIAs to be successfully deployed in multiparty social settings, they need to be aware of their surrounding environment and social context [Jung and Hinds 2018].

The F-Formation theory discussed in Section 17.2 also inspired work on automatic group perception, both from a model-based [Vázquez et al. 2015, Vázquez et al. 2017] and data-driven perspective [Hedayati et al. 2019, Swofford et al. 2020]. These methods demonstrated automatic detection of F-formations involving humans and robots and are illustrated in Figure 17.5. One of the challenges of group perception is feature extraction, especially when considering real-world environments. In this respect, Mead [2016] proposed a framework including different features (individual, physical and psychophysical) that can be automatically extracted and used to recognize proxemics and other social behaviors in HRI, e.g., interaction initiation and termination.

From a perception perspective, it is also important to recognize addressees in groups. Methods have leveraged sound source localization [Nakadai et al. 2008], visual focus of attention [Sheikhi and Odobez 2012, Sheikhi et al. 2013], and combinations of this data [Okuno et al. 2001, Vázquez et al. 2016]. Further, fusion and tracking of participants in interaction with SRs and IVAs has been investigated for the purpose of speaker identification, addressee detection and dynamic user entrance/leave mechanism [Yumak et al. 2014c]. To enhance multiparty dialogue management, attention management and addressee recognition can be enhanced by observing lip movement and gaze to successfully understand the current

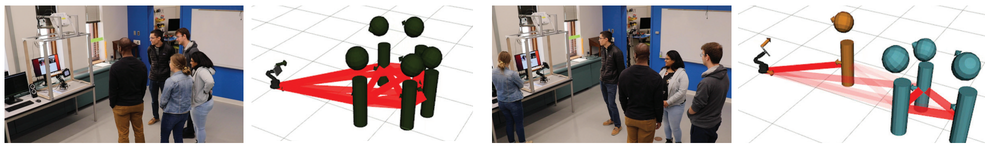

Figure 17.5 Conversational group detection in HRI [Adapted from Swofford et al. 2020]. The agents that have the same color are estimated to be part of the same group. The opacity of the red lines connecting the agents represents the likelihood of them belonging to the same group. Left: a situation in which all five people that interact with the robot are estimated to be part of its group. Right: an individual interacts with the robot while other people observe the interaction nearby.

addressee in the dialogue [Richter et al. 2016]. Further, Traum and Morency [2010] apply real-time visual processing to enhance a dialogue model of multiparty communication between humans and IVAs. Visual processing focuses on head orientation, nods and shakes to influence a multilayer dialogue model, including addressee identification, turn-taking, social affiliation and grounding.

Considering a different aspect of perception, interest has been developed in perceiving the dominant human in an interaction based on different sensor modalities. Skantze [2017] showed that analysis of dialogue with focus on the amount of speaking and turn-taking behaviors could help identify dominance early on in a conversation-based game. Strohkorb et al. [2015] utilized visual data only to predict the most dominant child in a group interaction.

17.3.3 Generating Behavior in Groups

The synthesis of small group behaviors involves automatic conversation management synchronizing a range of multimodal behaviors including speech, eye-gaze, gestures, and body positioning across group members in a socially appropriate manner. Locomotion behaviors support movements of individuals within the group, from small position shifts of group members that are natural in real situations, to the larger formation changes required to accommodate a newcomer to a group or coalesce when an existing member leaves. Generation also encompasses approach trajectories and join behaviors for newcomers to a group, an important ability supporting multiparty interaction with SIAs in both real and virtual environments.

Conversational Behaviors

In conversational group settings, humans use a variety of verbal and non-verbal signals to regulate, coordinate and otherwise manage their interactions. Figure 17.6 exemplifies situations in which conversational behaviors are explored.

Figure 17.6 Multiparty interactions involving (left) full-body conversational behaviors that reflect attitudes held by SIAs in virtual environments [©2021 Brian Ravenet] and (right) interactions between humans, SIAs and IVAs to investigate social presence [Pereira et al. 2014].

Eye-gaze (see Ruhland et al. [2015] and Admoni and Scassellati [2017] for reviews) is one important non-verbal behavior underlying conversation. A pioneering study by Mutlu et al. [2009] showed the importance of generating human-like gaze and how the appropriate robot's gaze can shape conversational roles. Considering groups with more than two people, Vázquez et al. [2017] showed how attentive robot gaze and body orientation should be generated jointly and the importance for the feeling of groupness. Further, more frequent short glances have been found to be more effective than less frequent longer stares for participants to feel the direction of look [Admoni et al. 2013].

Models for conversational behaviors have also been developed for IVAs. Prada and Paiva [2005] developed a model that supports the dynamics of a group of synthetic agents, inspired by theories of group dynamics developed in human social psychological sciences. Autonomous synthetic characters employing these models had a positive effect on the users' trust and identification with the synthetic group. Pejsa et al. [2017] present computational models of gaze and spatial orientation a virtual agent can use to signal specific footing configurations i.e. the non-verbal signals that conversational participants use to establish their roles.

Yumak et al. [2014a] investigate interactions between humans, SRs and IVAs in telepresence setups. Users may control IVAs and/or SRs or they may act autonomously, for example, in the case that their respective avatars i.e. users, leave the interaction. This is accomplished by means of an architecture that tracks multple users via audio-visual sensors and feeds the fused data into a dialogue manager that in turn generates virtual human and robot behaviors [Yumak et al. 2014b].

Ravenet et al. [2015] propose a model for the generation of non-verbal behaviors supporting the expression of interpersonal attitudes for turn-taking strategies and group formation in multiparty conversations among IVAs. Figure 17.6 (left) demonstrates a generated group interaction from this line of work.

More recently, de Coninck et al. [2019] employed a data-driven approach to automatically generate non-verbal behaviors for virtual characters during group interactions. Dynamic Bayesian Networks have further been used to establish associations between conversational state and non-verbal behaviors by analyzing the CMU Panoptic dataset [Joo et al. 2017].

In respect to empathy within groups, Alves-Oliveira et al. [2019] explore how the perception of the *emotional climate* can inform the generation of appropriate empathic behavior toward the group.

The selection of social actions by a robot in unstructured multiparty encounters was shown to be more successful and efficient when learned as an action selection policy through reinforcement learning [Keizer et al. 2013]. When treating these interactions in a task-based manner, knowledge-level planning has been shown to be promising [Petrick and Foster 2013].

A further line of research explores how an SR can be part of joint action with a group of humans, e.g. dancing in a group. Anticipatory action planning was necessary to allow a robot to join a jazz combo [Hoffman and Weinberg 2011]. Iqbal et al. [2016] found that perceiving high-level human behavior to anticipate human group motion is advantageous when generating motion for joint actions with humans. The behavior of the robot or multiple robots when joining a joint action has further influence on the group dynamics specifically if the two robots generate their motion according to different paradigms [Iqbal and Riek 2017b].

Locomotion Behaviors

Locomotion is a desirable capability for robust situated multiparty interactions in which artificial systems are expected to be mobile, active conversational participants that adapt to humans rather than static, passive systems. Social-aware navigation (see [Charalampous et al. 2017] for survey) enables agents to navigate in the environment so that they not only establish the fastest path to a goal, but also respect other characters as social entities.

Thus far, social-aware methods have been mostly applied to the socially acceptable navigation of robots. Sisbot et al. [2007] proposed a human-aware robot motion planner to generate a safe path by considering the human position, gesture and field of view. Gao et al. [2017] and Pokle et al. [2019] proposed approaches that combined classical planning with modern deep learning techniques to enable SRs to adapt to dynamic human environments. Satake et al. [2013] presented a method for a robot to approach people who are walking through the environment. Other social-aware navigation systems consider static human groups. Truong and Ngo [2018] proposed a framework to enable an SR to approach a human group safely and socially. Yi et al. [2015] presented a cost map based on the distance for mobile pedestrians and static groups. Gómez et al. [2014] extended a fast-marching algorithm to navigate a robot for engaging a group of people. Social-aware navigation methods have also been applied to virtual agents. Pedica and Vilhjálmsson [2018] simulated human territoriality while navigating a virtual character toward small groups. A recent work [Yang and Peters 2019c] proposes

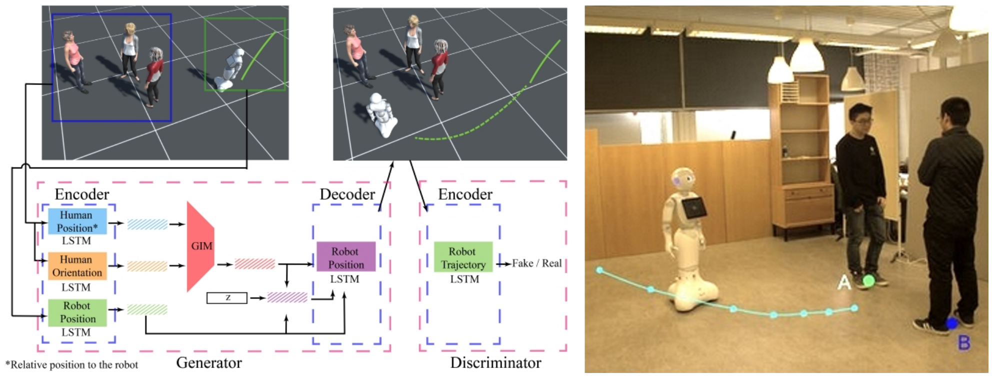

Figure 17.7 Machine learning models for generating approach behaviors into small groups for SIAs, including Generative Adversarial Networks-based model (left) [Adapted from Yang and Peters 2019b] and reinforcement learning-based model (right) [Gao et al. 2019].

a social-aware navigation system capable of moving an agent through an environment that contains both static and moving virtual groups.

Repiso et al. [2020] used an adaptive side-by-side model so that a robot could autonomously accompany a group of people walking.

Approach Behaviors

Several studies have been carried out that specifically concern the approaching behaviors of newcomers into small free-standing conversational groups. Examples for these approaches are given in Figure 17.7. Ramírez et al. [2016] adopted inverse reinforcement learning, involving several participants demonstrating approaching behaviors for a robot to learn. Samarakoon et al. [2018] designed a method to replicate the natural approaching behaviors of humans. In a recent work, Gao et al. [2019] proposed a deep reinforcement learning model to generate robot approaching small group behaviors. Behaviors for approaching groups have also been studied for IVAs. Jan and Traum [2007] presented an algorithm for simulating movement of agents, such as an agent joining the conversation. Pedica and Vilhjálmsson [2012] integrated behavior trees in their reactive method to simulate lifelike social behaviors, including robot behavior for approaching groups. Both approaching and leaving behaviors for virtual characters were considered by Yang et al. [2017]. In this work, a finite state machine is utilized in the transitions between different social behaviors. More recently, Yang and Peters [2019b] proposed a model based on Generative Adversarial Networks (GAN) to generate safe and socially acceptable trajectories into free-standing conversational groups. The trajectory prediction model considers group dynamics, including the changing position and orientation

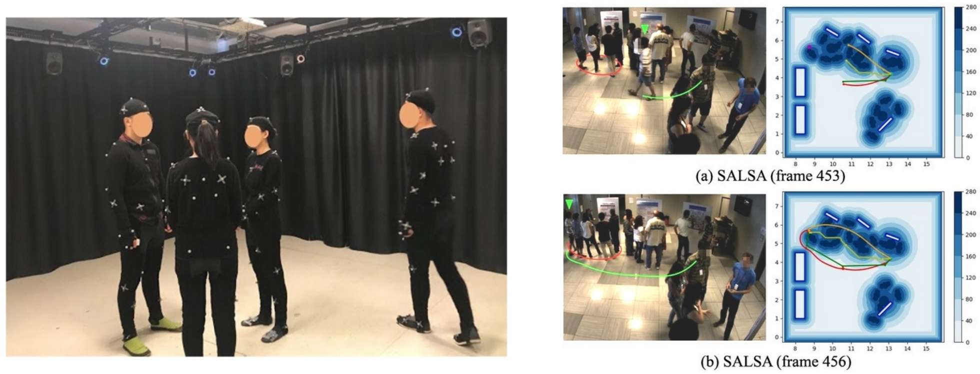

Figure 17.8 Full-body motion capture data of approach behaviors (left) [©2020] and the approach behaviors from real-life datasets (right) [Yang and Peters 2019a].

information of group members as they make position adjustments within a formation, and is intended for application to both virtual agents and mobile robots.

17.4 Group Datasets

To inform either the perception of group dynamics or generation of appropriate SIA behavior, datasets capturing different aspects of multiparty interaction have been collected. Relevant datasets can be divided into human-robot and human-human datasets.

Only a few datasets exist that capture multiparty interactions with at least one robot. The *Vernissage Dataset* [Jayagopi et al. 2013] captures interactions of multiple participants with a wizarded NAO robot. The *UE-HRI* dataset focuses on spontaneous engagement with a Pepper robot and contains dyadic and multiparty interactions [Ben-Youssef et al. 2017]. In addition, *MHHRI* [Celiktutan et al. 2017], focuses on analyzing personalities and relationships with engagement of human-human (dyadic) and human-robot interactions (triadic). A recent dataset *CongreG8* [Yang et al. 2020] uses full-body Motion Capture (MOCAP) with a focus on approach and joining behaviors for free-standing conversational groups, and includes both human-human data and human-robot data that have been applied to both virtual agent and robot group scenarios. Examples for approach behaviors covered in *CongreG8* and other datasets are given in Figure 17.8.

Human-human interaction databases in contrast to multiparty human-robot datasets were extensively reviewed in several surveys including Borges et al. [2013], Stergiou and Poppe [2018], Zhang et al. [2019]. Unlike datasets containing individual action recordings, human-human interaction datasets, i.e. those containing multiple humans interacting, are relatively scarce. The *CMU Panoptic* dataset [Joo et al. 2017] collects 3D full-body motion of a group of people in various social interaction scenarios such as dancing and haggling. The *BARD* dataset [Cancela et al. 2014] focuses on recording human behavior analysis in video sequences with multiple targets in wild environments. Other datasets involving groups collect 2D location information such as body position and orientation information. The *MatchNMingle* dataset [Cabrera-Quiros et al. 2018] is a multisensor resource for the analysis of social interactions and group dynamics. The *IDIAP Poster* dataset [Hung and Kröse 2011] is a video dataset with annotations of body position and orientation information, but also the data for F-formations (conversational groups). Similarly, the *Coffee Break* dataset [Cristani et al. 2011], the *SALSA*[1] dataset [Alameda-Pineda et al. 2015], and the *Cocktail Party* dataset [Ricci et al. 2015] contain F-formation annotations and 2D pose information. The *VEIIG* dataset [Bandini et al. 2014] collects annotated data with moving groups in a crowd. The *Semisynthetic* dataset [Yang and Peters 2019a] contains trajectories of individual agents approaching groups based on a social-aware navigation method, and it is used to learn approaching group behaviors. Further, the *Elea* dataset consists of multiparty human-human of three and four participant groups where the recorded data allows the identification of emerging leadership in a survival task [Sanchez-Cortes et al. 2012]. A large set of meetings captured through multiple modalities are available in the *AMI meeting corpus* [Kraaij et al. 2005]. A more playful setting was chosen in the *WOLF* dataset [Hung and Chittaranjan 2010] where larger groups engage in the Werewolf game. Audiovisual data of multiparty interaction in three different cultures and languages was captured and annotated in the *UTEP-ICT* dataset [Herrera et al. 2010].

17.5 Similarities and Differences in IVAs and SRs

Considering previous research, in this section we identify and discuss a number of aspects that IVAs and SRs have in common regarding their ability to work in groups. It is important to note that others have conducted similar analyses before. For example, Gratch et al. [2015] discussed how research implications on virtual humans can impact human-robot teamwork. We begin by discussing the similarities:

- **Driven by user experiences.** Both in the virtual or the physical world, many SIAs are developed to evoke realistic or interactive user experiences. Given this similar goal, it is often the case that common metrics are used to evaluate people's experiences with these agents. Social presence, for example, has been extensively investigated in both IVA [Hai et al. 2018] and SR [Pereira et al. 2014] multiparty user studies.
- **Application domains.** Many SIAs share the same application domains (e.g. entertainment, gaming, therapy, collaboration, etc.), offering opportunities to share computational models between the two sub-communities. While there are some exceptions to this (e.g. navigation algorithms in virtual worlds differ significantly from the ones for real-world environments), many of the perception and high-level decision-making components could be implemented in a way that the target agent embodiment is abstracted.

[1] https://www.fbk.eu, https://tev.fbk.eu/salsa

For example, as discussed by Gratch et al. [2015], SIAs natural language dialog systems could be adapted for SRs and vice-versa.

- **Multimodal perception and social behavior generation.** While the sensing capabilities and embodiment of IVAs and SRs might differ, all SIAs benefit from multimodal perception and behavior generation. Multimodal perception is key for making agents more robust and capable of dealing with the complexity of group interactions. For example, perception of multimodal cues has been fundamental for keeping track of turn-taking patterns and advancing multiparty dialog [Richter et al. 2016, Traum and Morency 2010]. Likewise, multimodal behavior generation is important for providing effective communicative signals to users. As in human interactions, enabling SIAs to communicate through multiple modalities can facilitate important communicative processes like grounding [Mehlmann et al. 2016]. But care must be taken when designing multimodal behaviors. Research has shown that different behavior modalities, like body motion and gaze, can influence how people perceive each modality during group interactions [Vázquez et al. 2017].

We continue by discussing the differences:

- **Perception.** While we perceive the physical environment directly via our visual senses, there is a significant level of indirection when rendering the virtual scenes in which IVAs are embedded. Hardware limitations and the choice of virtual camera parameters may result in different perceptual impressions of virtual representations when compared to their real counterparts. For example, differences in distance and social space perception in virtual [Li et al. 2019] and mixed reality [Li et al. 2018] environments may result in different interpersonal distances being observed between humans and IVAs when compared to real-world situations. Differences may also exist in how we perceive a host of other factors, such as the appearance [Peters et al. 2018] and photorealism of the IVAs (see Embodiment below), which may also impact the degree to which we treat IVAs as social entities. Especially for multiparty interactions, considering these effects combined with how humans perceive groups as entities i.e. group entitativity, seems important for creating perceptually sensitive social models of behavior [Bera et al. 2018] transferable between the virtual and real worlds.
- **Mobility.** There are extra considerations for SRs if they are to be mobile to any degree in their environments. Especially, the priority for SR movement algorithms is that they should be safe and efficient when operating in the vicinity of humans. Physical multiparty interactions, which imply numerous humans and SRs interacting in close proximity to each other, are therefore especially challenging. In contrast, IVAs have direct access to the state of the virtual environment through a world database and collisions with humans

are only significant in relation to the visual plausibility of the simulation as they do not have any physical consequences.

- **Embodiment.** A core difference between SRs and IVAs is their embodiment: real versus virtual. The impact of embodiment on social presence in multiparty interactions [Shamekhi et al. 2018] is especially significant due to how social presence pervades interaction, from proxemics to attention behaviors [Goffman 1963]. While favorable effects of social presence have been attributed to physical embodiments, the role of physical presence in the process warrants investigation [Li 2015, Thellman et al. 2016]. For IVAs, the photorealism of the embodiment impacts self-reported impressions of social presence [Zibrek and McDonnell 2019], although questions remain as to what degree coinciding behavioral effects, such as those observed in human proxemic behavior, can be achieved based on photorealism improvements alone.
- **Gaze.** Perception of mutual gaze displayed by SIA in multiparty interactions is of specific importance as it is connected to successful turn-taking. When considering IVAs that are displayed as 2D agents on a screen in a physical environment, Al Moubayed et al. [2012] argue that the Mona Lisa effect has stronger impact in the interaction with multiple users. They compared a displayed 2D agent to a 3D back-projected robotic head and found that the 3D agent was perceived as less confusing in turn-taking. Further evidence on the importance of physical movement on gaze was found by Vázquez et al. [2017] where the robot's body motion could help to convey the gaze behavior. More recently, a more subtle change in eye gaze display was found influential by Kinoshita et al. [2017] where convex eyes could direct gaze more accurately and hollow eyes were correlated with a broader gaze cone.

17.6 Current Challenges and Future Directions

In this section, we discuss some of the current challenges in multiparty interaction between humans and SIAs, along with future research directions.

- **From one-to-one to one-to-many**. Most of the previous research on computational models for perceiving and generating social behavior in SIAs has focused on dyadic interactions of one agent and one user. However, group interactions tend to be more complex [Traum 2004], and the number of people around the agent not only affects how the agent should behave but also how it should perceive its environment. So far, little is known about how data-driven models perform when tested in a group size different than the one they were trained on, and most data-driven perceptual systems for human-agent interaction rely on data collected in the same context where future interactions are likely to occur. While previous work has shown that a disengagement classification model trained with group data generalized better to individual participants than the reverse

[Leite et al. 2015], further research is needed to confirm that the same findings apply to other types of multiparty perception and decision-making systems.

- **Formation changes and situated interactions**. Real-world multiparty interactions involve a degree of mobility of participants due to small shifts in the positioning of group members who are never totally static. Moreover, explicit formation changes, which may be caused by members joining and leaving the group, or even a change in the attitudes or the focus of attention of the group, can bring additional challenges. Dynamic positioning behavior therefore needs to be considered in conjunction with full-body behaviors and conversational management since current research typically assumes static SIAs in multiparty situations. This places a higher priority on understanding the impact of environment constraints on human proxemics behaviors, in addition to developing artificial models capable of better understanding their spatial environments so that they can account for such changes while also solving challenging locomotion problems.
- **Individual and group adaptation**. SIAs developed for multiparty interaction need to find an optimal balance between adapting to an individual or the whole group. When considering individual adaptation within a group, the behavior of other group members can still be useful for better responding to the individual. Pioneering work in this direction by Mou et al. [2019] has shown that group information can be used, for example, to improve the accuracy of recognizing an individual's affective state in the group. However, despite some efforts in this direction, questions such as how to accommodate for social norms, culture, and individuality of group members [André et al. 2020] remain largely unexplored.
- **Dynamic social environments**. Laboratory environments are extremely valuable for controlled human-agent interaction experiments (e.g., for investigating specific system components in isolation), but the way people behave in laboratory conditions is substantially different from that of the real world. If SIAs are to be placed in complex, constrained and/or unstructured social settings, more in-the-wild research is needed in those settings from the early stages of development. As discussed by Jung and Hinds [2018], it is particularly important to understand the impact of the robot (or agent) on the social environment beyond the individual. Multiparty interactions also need to be robust to individuals joining and leaving them, placing additional importance on modeling social active vision mechanisms [Breazeal et al. 2001, Peters et al. 2011] so that those within the group become aware of potential newcomers and are capable of interrupting ongoing interactions in order to allow them to join in a socially appropriate manner.
- **Choice of metrics.** To measure the influence of robot behavior on groups, different aspects have been found of interest to study. For example, works that consider social aspects of group dynamics [Fraune et al. 2017a, Sebo et al. 2020, Short and Mataric 2017,

Strohkorb Sebo et al. 2018] have used different questionnaires and interviewing techniques to measure inclusion, cohesion, entitativity, or psychological safety. To further understand different SIA behaviors and their influence in multiparty contexts, new valuable insights could be gained by identifying and utilizing standardized metrics for varying multiparty human subject studies. Abrams and Rosenthal-von der Pütten [2020] take a first step in this direction by discussing aspects of cohesiveness, entitativity and group identification and how to measure these aspects. However, further challenges might arise in specific group contexts, e.g in cases where language is no option, for example, among young children or children with varying mother tongues. So far, no validated methods exist that could measure, e.g. the cohesiveness of a group, other than through questionnaires or interviews. The development of language-free tools could further give insights into group dynamics in special target groups or generally allow for indirect assessment, which has been found to give valuable additional insight for other metrics (e.g., trust [Glaeser et al. 2000]).

- **Replicability of results.** As discussed by Iqbal and Riek [2017a], the community still lacks an infrastructure to support replicability that is of specific importance in more complex environments such as multiparty interactions. Therefore, it is difficult to explore the effects of different kinds of robots in comparable situations. Recently, Jung et al. [2020] proposed a task that allows the studying of the effect of resource distribution pursuit by a robot and that might allow comparing the effects of different robots and robot behaviors across research groups.

17.7 Summary

In this chapter, we addressed multiparty interactions with SIAs. We provided an overview of the common methods and approaches from social psychology that can be useful for defining the scope and understanding of group behaviors. We then reviewed existing works addressing different aspects of multiparty interactions. Among IVAs, the believability of these agents and how they act in groups has been discussed. When considering the interaction of SIAs and humans in groups, their behavior has been shown to affect the group dynamics and attitudes humans develop about the SIAs. Further, SIA behavior can be used to explicitly influence the dynamics of a group and their interaction. However, to be able to interact in groups, SIAs need to be able to firstly perceive the group and its dynamics. To further allow autonomous interactions, SIAs need to be capable of generating appropriate behavior. We discussed how the F-formations, the group's focus of attention, the addressee in a conversation and interpersonal dominance can be detected. Further, we reviewed the generation of appropriate gaze behaviors and socially aware motions. To help the perception and generation of group behaviors, we presented a list of relevant datasets. Similarities like multimodal perception of groups and their dynamics, high-level decision making and multimodal behavior generation offer opportunities for the two communities to find symbioses. There are still many open research directions in this field. We ended with a discussion of current challenges and future research directions such as coping with changes in group dynamics, and the applicability of models and methods from individuals to groups or vice versa.

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