HOW PARTICIPATORY METHODS FACILITATE SOCIAL LEARNING IN NATURAL RESOURCE MANAGEMENT

AN EXPLORATION OF GROUP INTERACTION USING INTERDISCIPLINARY SYNTHESES AND AGENT-BASED MODELING

Thesis

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Summary

The idea of social learning embraces many promises. Social learning is expected to address the complexity of natural resource management, to foster behavioral change, and to promote collective action (Muro & Jeffrey, 2008; Pahl-Wostl, 2006). Through social learning the flexibility of socio-ecological systems and thus their ability to respond to and act upon change can be enhanced (Pahl-Wostl & Hare, 2004). Although frequently used, a commonly agreed upon definition for social learning as well as a shared understanding of the processes it entails is still missing (Muro & Jeffrey, 2008; Reed et al., 2010; Rodela, 2013). Participatory processes are seen as a means to foster social learning (Muro & Jeffrey, 2008). While there is a large body of literature on social learning and participation in natural resource management (e.g., Stringer et al., 2006; Tàbara & Pahl-Wostl, 2007), the lack of a common framework for measurement and comparison and an explicit definition hamper a comparison of research on successful social learning as well as on the processes fostering or hampering it (Muro & Jeffrey, 2008; Reed, 2008; Reed et al., 2010). Furthermore, there remains the need for research on the building of a shared understanding and factors or processes influencing this. Nevertheless, because social learning entails individual learning it is hard to measure (Muro & Jeffrey, 2008).

In this thesis, the central interest is social learning facilitated through interactive settings within participatory processes. More specifically, I make an effort to better understand how participatory methods applied during participatory processes in natural resources management can serve as nuclei for social learning. Thereby, my main focus is on learning via interaction in groups. My approach begins with the aim of developing an analytical framework which reflects the main processes that are effective within participatory methods. The framework presents an analytical tool, including proposed methods to monitor and compare the results of participatory approaches with respect to social learning. Building upon this framework, I develop an agent-based model to simulate and explore group dynamics. This model is intended to support a theoretical exploration of whether or not and if so, at what stage, personal views of a problem evolve into a shared understanding of a problem (which can be seen as a key element of social learning), and an assessment of how individual mental models and group properties relate to each other. Results of the model are interpreted to offer suggestions about factors hindering or fostering social learning during the application of participatory methods.

The research interest in this thesis can be summarized in 3 research questions:

- RQ1: (How) does social learning occur during the use of participatory methods within resource management?
- RQ2: How can social learning processes facilitated through participatory methods be reproduced in an agent-based model to gain a deeper understanding of involved processes and feedback?
- RQ3: Is it possible to identify factors or processes that hamper/ foster social learning in participatory methods through model exploration?

This thesis is written as a cumulative work, comprising a framing document and four research articles presented in Chapters 4 to 7. The papers belonging to this thesis are:

- **Paper I**: Scholz, G., Dewulf, A., & Pahl-Wostl, C. (2014). An analytical framework of social learning facilitated by participatory methods. *Systemic Practice and Action Research*, 27(6), 575-591. DOI:10.1007/s11213-013-9310-z
- **Paper II**: Scholz, G., Austermann, M., Kaldrack, K., & Pahl-Wostl, C. (2015). Evaluating group model building exercises: a method for comparing externalized mental models and group models. *System Dynamics Review*, 31(1-2), 28-45. DOI: 10.1002/sdr.1538
- **Paper III**: Scholz, G., Pahl-Wostl, C., & Dewulf, A. (2014). An Agent-Based Model of Consensus Building. In *Social Simulation Conference*. DDD repository: http://ddd.uab.cat/record/125597
- **Paper IV**: Scholz, G., Dewulf, A., & Pahl-Wostl, C. Social learning in an agent-based model: Using cognitive biases to simulate learning and consensus finding in group discussions. Working paper

The framing document provides an overview of the conceptual foundation and the theoretical background this thesis builds upon. It therefore embraces a literature review of relevant fields, including research on social learning, participation and group processes, a short introduction to exploratory agent-based modelling, and concepts which are useful for modeling group interaction. While a commonly agreed upon definition for social learning as well as a shared understanding of entailed processes is still missing (Muro & Jeffrey, 2008; Reed et al., 2010; Rodela, 2013), there is a great deal of activity currently with respect to specifying and synchronizing social learning approaches. Most of the recent approaches to measuring social learning focus on cognitive learning while neglecting the social-relational dimensions of learning. This is a challenge for future research because relational aspects are an important element of most conceptualizations of social learning, including issues like trust and the building of relationships. Another finding is that the social processes occurring within participatory processes are an important influence and may hamper or foster social learning in participatory settings. Little knowledge exists about the social dynamics in the process of social learning (Sol et al., 2013). Thus, investigating group interaction and resulting dynamics is an important endeavor for a better understanding of social learning. Two important features to consider are the tendency of individuals to conform to what they perceive as the views of the majority, and the influences of power relations. However, these issues are not particularly easy to investigate in empirical case studies. Here, agent-based modeling can provide a possibility for exploring the dynamic interplay of different assumptions. The agent-based model which is part of this thesis has two main purposes: the integration of knowledge from various strands of research, and the exploration of dynamics that may occur during the application of participatory methods. Exploration means the specification of rules at the micro level, the agents, and the identification of dynamics that occur in the model run with different parameterizations.

Paper I points out that learning through interaction does not necessarily lead to a shared understanding of a particular topic. Shared understanding refers here to the degree of similarity between the mental models of participants of a participatory method. Starting from the definition in Reed et al. (2010) I added another dimension, the direction of learning, being either convergent or divergent, to enhance the analysis of learning processes. Convergent learning refers to an increase in shared understanding, and means that actors integrate new perspectives gleaned from each other, and/or develop new shared concepts. The analysis of the direction of learning is facilitated through the use of the mental model concept. I provide a short review of mental models, learning via conceptual change and the shift and emergence of roles; and integrate these concepts into an analytical framework of social learning facilitated by participatory methods. The developed framework provides a conceptual basis for the analysis of social learning facilitated by participatory methods. Furthermore, I propose indicators to measure if social learning occurred during the use of participatory methods and discuss methods for measurement.

Paper II supplements methods discussed in Paper I by proposing a method to evaluate group model building sessions by comparing externalized individual mental models and a group model. The method can be used to evaluate: (i) if all participants were able to include their point of view (this point can be complemented by a questionnaire), (ii) how the facilitator performed in managing the dominance of certain participants, and (iii) if new concepts emerged out of the process which no participant mentioned before, leading to innovation. The methods presented in this paper allow for a comparison of all representations of mental models including concepts and a group model. Thereby, the first step includes a categorization of included concepts in order to be able to subsume similar concepts. This is a delicate process. After the process of categorization data is displayed in a matrix, and reordered with the help of the Rank Order Clustering algorithm (King, 1980). The resulting matrices can be used to answer a series of research questions proposed for evaluation. Venn diagrams are proposed as an additional option for displaying data, which is particularly useful for smaller groups of up to five participants.

Paper III and IV present results from the agent-based model CollAct. CollAct is an effort to provide a basic model of group discussions considering both cognitive and relational knowledge and learning. Agents in CollAct, modeled as participants, discuss an abstract issue and try to reach a consensus. This could, for example, be the definition of the problem scope, a management plan, or suggestions for measures that could be implemented. Probably the most interesting aspect of CollAct is the explicit modeling of the mental models of the participants, comprising both a substantive and a relational model. In both of these models learning can take place, and both are used to interpret incoming messages and decide upon further actions. CollAct is based upon the analytical framework developed in Paper I, which I adjusted to the context of a group discussion. To analyze the simulation output the indicators developed in Paper I as well as the measures developed in Paper II are incorporated into output indicators. CollAct produces discussions with successional clusters of messages on the same topic. Furthermore, a

change of topic, different levels of controversy, learning, the development of a shared understanding, and the shift and emergence of roles are reproduced in the model. Factors identified as having an important influence on the composition of the consensus and on the amount of learning include: ending time of the discussion, group size, level of controversy within the discussion, cognitive diversity and available knowledge, existence of a leading role at the outset (this influence depends on the group size), and conformity.

A strength of CollAct is that it not only models social contagion, but also includes individual learning to simulate the building of a shared understanding. It therefore allows for an exploration of the relationship between the building of consensus and the development of a shared understanding. In CollAct both the level of controversy and the level of conformity have an important influence. While this influence is not 'the more the better' controversy and conformity should be balanced in a cautious way which presents a challenge for the facilitation process. Furthermore, results suggest that substantive (cognitive) learning is needed to build a shared understanding, while conformity and relational influences are sufficient conditions for achieving a consensus that is not linked to the development of a shared understanding. Thus, to exploit the expected benefits from participation to foster the building of a shared understanding, and to foster the endurance of achieved decisions (effectivity claim), it is important to engage in cognitive learning. Another conclusion is that high mutual esteem and the building of a shared understanding reinforce each other. Sol et al. (2013) describe trust, commitment and reframing as emergent and interrelated aspects that occur in the process of social learning and influence each other and the ongoing process. CollAct can serve as a thinking-tool to explore such ideas. Looking at the practice, the building and maintaining of high mutual esteem in the form of good relationships may serve as an enforcing factor for social learning. Hence, investing in a good atmosphere and leaving space for relational learning may result in net benefits even in terms of cognitive learning in the long run.

A next step is the comparison to and testing through empirical research. The framework developed in Paper I is intended for use in empirical research and the comparative analyses of case studies. The same applies to the methods developed in Paper II, which can be used to complete analyses conducted with the help of the framework, or as a stand-alone method to evaluate group model building processes. I suggest group model building as an initial application area for the framework, because the method presented in Paper II could be integrated and the full analytical potential of the framework may be exploited. Additionally, interesting influences and processes can be simulated in the model, which can be run with the data provided by the case studies. In this way, results of CollAct can be compared to the evaluation of case studies, and further model validation and insights to the specific case studies are possible.

It would be highly interesting to link the results of this thesis to approaches treating wider social units, such as network analyses. A network analysis provides a complementary understanding of learning processes especially at the group and network levels through formal quantitative analyses (see for example, Bodin & Crona, 2009; Methner, forthcoming; Newig et al., 2010).

When looking at the influences of social learning in the wider social context, the direction of learning (being convergent or divergent) is important as well. Divergent learning may spread new ideas and increase the number of possible options, while convergent learning is linked to social learning as defined within this thesis, allowing for the building of a shared understanding that may lead to collective action and change.

CONTENTS

FIGURES AND TABLES IN FRAMING DOCUMENT

"To me, however, the most important contribution of the modeling enterprise—as distinct from any particular model, or modeling technique—is that it enforces a scientific habit of mind, which I would characterize as one of militant ignorance—an iron commitment to "I don't know." That is, all scientific knowledge is uncertain, contingent, subject to revision, and falsifiable in principle. (This, of course, does not mean readily falsified. It means that one can in principle specify observations that, if made, would falsify it). One does not base beliefs on authority, but ultimately on evidence. This, of course, is a very dangerous idea. It levels the playing field, and permits the lowliest peasant to challenge the most exalted ruler—obviously an intolerable risk." (Epstein, 2008, p.4)

1 Introduction

The importance of natural resource management to sustainable development is manifested through the overexploitation of natural resources and the increasing number of social conflicts originating from their unsustainable use (Rammel et al., 2007). Furthermore, the increase in population confronts declining resources, amplifying the pressure on managing natural resources sustainably. The traditional approach of coping with this challenge is through top-down, command and control management (Holling & Meffe, 1996). However, if the focus is on the efficiency of control, the managing system becomes isolated from the managed system and inflexible in its structure, and is therefore unable to recognize and react to ecological change or collapse (Holling & Meffe, 1996). Challenges in natural resource management include multiple users and multiple uses of resources, temporal trade-offs, unclear or open access property rights, imperfect markets, and external influences (Grimble & Wellard, 1997). Natural resource management is characterized by a high level of complexity and uncertainty, and the need to address sustainability conflicts at local to global levels (Rammel et al., 2007). Hence, further command and control cannot provide appropriate solutions to these issues; more flexible approaches are needed (Holling & Meffe, 1996). These new approaches need to cope with various temporal, spatial, and social scales, multidimensional interactions, and irreducible uncertainties (Rammel et al., 2007).

In the last decade there has been a change in the paradigm of natural resources management (Pahl-Wostl et al., 2011; Pahl-Wostl et al., 2007). As a consequence, water resources management is shifting away from relying on hierarchical processes dominated by state actors and on technical, sectoral solutions towards an integrated water resource management, placing an increased focus on governance, adaptation, and complexity (Pahl-Wostl et al., 2007; Pahl-Wostl et al., 2008). In particular, human dimensions are increasingly considered important: instead of exclusively relying on expert knowledge to develop management practices, stakeholder involvement is being promoted (Mostert, 2003; Pahl-Wostl et al., 2007, Pahl-Wostl et al. 2011). Participation is thereby seen as an answer to the need for flexible decision making by embracing a diversity of knowledge (Reed, 2008).

Claims for participation and social learning[1] are closely linked (Muro & Jeffrey, 2008). Social learning has gained increasing attention as an important part of sustainable natural resource management (e.g., Mostert et al., 2008; Muro & Jeffrey, 2008; Pahl-Wostl, 2006; Reed et al., 2010; Schusler et al., 2003). Through social learning the flexibility of socio-ecological systems and thus their ability to respond to and act upon change can be enhanced (Pahl-Wostl & Hare, 2004). Furthermore, social learning is expected to address the complexity of natural resource management, to foster behavioral change, and to promote collective action (Muro & Jeffrey, 2008; Pahl-Wostl, 2006). Although frequently used, social learning is not clearly specified as

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[1] A detailed definition of social learning is discussed in Section 2.1.2.

theory or process (Muro & Jeffrey, 2008). A commonly agreed upon definition for social learning as well as a shared understanding of entailed processes is still missing (Muro & Jeffrey, 2008; Reed et al., 2010; Rodela, 2013).

A positive example of social learning facilitated through participation is reported by Stringer et al. (2006) in their conclusion on a case study on the establishment of a National Park in Austria, where

> *"[…] traditional top-down approaches were, for the most part, ineffective, supporting the need for pragmatic, substantive, and normative participation in social– ecological system management. Only by fostering communication and learning among stakeholder groups, decades after the idea for a National Park was proposed, was consensus reached on the establishment of the park."(Stringer et al., 2006, p.14)*

Thus, participation enabled the discussion of different perspectives, problems, and goals (Stringer et al., 2006). The integration of problem perspectives from a range of actors helped to overcome a block in natural resource management.

While there is a large body of literature on social learning and participation in natural resource management (e.g., Ison et al., 2004; Muro & Jeffrey, 2008; Reed, 2008; Stringer et al., 2006; Tàbara & Pahl-Wostl, 2007), the lack of a common framework for measurement and comparison and an explicit definition hamper a comparison of research on successful social learning as well as on the processes fostering or hampering it (Muro & Jeffrey, 2008; Reed, 2008; Reed et al., 2010).

In a review of the theory and application of social learning in participatory natural resource management, Muro and Jeffrey come to the following conclusion:

> *"There still remains much to learn about the more fundamental questions in relation to social learning, namely whether participatory processes lead to a shared understanding of the circumstances on which agreement and action can be based, which process features and context factors foster or inhibit this change and how it contributes to process outcomes. This poses a number of serious challenges because first the literature suggests that social learning involves internal changes which are generally hard to qualify and measure, and second the lack of a consistent concept of social learning complicates the task of defining common indicators to measure social learning as either process or outcome."* (Muro & Jeffrey, 2008, p. 340)

In this thesis I address both of these challenges. This thesis is written as a cumulative work, comprising a framing document and four research articles. In Paper I (Chapter 4) I address the second challenge, starting with a definition of social learning proposed by Reed et al. (2010). Weak aspects of the definition are discussed and an amendment to it is suggested. Furthermore, I propose indicators to measure whether or not social learning occurred. Where methods were

missing to measure the suggested indicators, I develop and test them in Paper II. This is the case for the comparison of externalized individual mental models[2] and a group model.

With respect to the first challenge, Muro and Jeffrey state that internal changes involved in social learning processes are difficult to measure and qualify. The interaction of stakeholders with various types of knowledge and the resulting dynamics can be explored through an agent-based model. In this thesis I develop an agent-based model, CollAct, in which internal changes in individuals are explicitly modeled and can be tracked over time. This *in silicio* exploration of processes generating social learning is helpful for integrating different concepts, operationalizing them, and exploring the results of the dynamic interactions of processes. In summary, modeling social learning facilitated through a participatory process has two main advantages:

i) A common problem in research is that disciplinary boundaries hamper the diffusion and efficient use of already-generated knowledge. The modeling of complex phenomena often requires the inclusion of knowledge from more than one discipline. Modeling allows (and often requires) integrating knowledge across disciplinary boundaries.

ii) An exploration using different rules and parameters allows the definition of a set of rules (theoretical assumptions) that are sufficient to reproduce certain patterns. Accordingly, the consequences of different assumptions about [xyz] and their dynamic interplay can be explored.

In this thesis I adopt a descriptive (rather than normative) perspective on social learning, focusing on the following questions: (i) what is happening at which stages of the social learning processes?; (ii) what is expected to happen based on the theoretical assumptions for the modeling exercise?; (iii) which factors may be of advantage or disadvantage for fostering such processes. Furthermore, the focus of the agent-based model is on group discussions. This is only one step in social learning processes and neglects the dissemination of results to wider social units. Nevertheless, the focus on a single event to limit context factors is a reasonable strategy (Raadgever, 2009). The process in participatory endeavors has been found to have a strong influence on results, possibly stronger than the specific methods chosen (Reed, 2008). These are well suited arguments for exploring group processes and their underlying rule sets in a model.

To model participatory processes, I was able to rely on an exhaustive body of literature dealing with social learning, group processes, and social-cognitive effects. Therefore, this thesis can be seen as an integrative approach that recombines findings across disciplinary boundaries (e.g., natural resources management research, operational research, psychology), and which models them in a way that allows linking various findings through simulated processes. Thus, effects

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[2] Mental model refers to personal internal representations of the surrounding world. Mental models are discussed in Section 2.4.2.

resulting from the combinations of different theoretical assumptions can be studied and compared with reality.

The remainder of this chapter introduces the aim of this thesis, which translates into three research questions (section 1.1), and provides an outline of the thesis' content (Section 1.2).

1.1 AIM OF THE THESIS AND RESEARCH QUESTIONS

The central interest of this thesis lies on social learning facilitated through interactive settings within participatory processes. More specifically, I make an effort to better understand how participatory methods applied during participatory processes in natural resources management can serve as nuclei for social learning. Although I take the broader scope of social learning theories into account, my main focus is on learning via interaction in groups. My approach starts with the aim of developing an analytical framework which reflects the main processes that are effective within participatory methods. The framework presents an analytical tool, including proposed methods to monitor and compare the results of participatory methods with respect to social learning. Building upon this framework, I develop an agent-based model to simulate and explore group dynamics. This model is aimed at a theoretical exploration of whether and when personal views of a problem evolve into a shared understanding of a problem (which can be seen as a key element of social learning), and an assessment of how individual mental models and group properties relate to each other. Results of the model are interpreted to offer suggestions about factors hindering or fostering social learning during the application of participatory methods.

The aim of this thesis is translated into three research questions (RQ) specified below. RQ1 focuses on addressing the current state of research and setting the theoretical foundations of this thesis. RQ2 covers the development of a model which is built upon the theoretical foundations dealt with in responding to RQ1. Finally, RQ3 aims at an evaluation of model results and their use in addressing issues discovered through RQ1.

The three research questions are briefly described along with a link to the part of this thesis embracing it, and split into 'smaller' sub-questions. All research questions are answered by addressing the respective sub-questions in the conclusions chapter of this thesis.

RQ1: (How) does social learning occur during the use of participatory methods within resource management?

RQ1 addresses the main question if, and if yes how, social learning can be facilitated during the application of participatory methods. To answer this question, I conducted a literature review, results of which are in Chapter 2, to be able to discuss recent empirical evidence for this

claim. For further analysis, a definition of both social learning and participatory methods is needed, as well as indicators that denote whether or not social learning occurred. This endeavor is presented in Chapter 2 and Paper I. To measure the proposed indicators, methods are needed. I present methods to measure indicators for social learning in Papers I and II. Finally, the elements and processes important for social learning facilitated through participatory methods are discussed in Chapter 2 and Paper I, and factors hampering or fostering social learning are identified in Chapter 2. Sub-questions used to structure my research are:

a. What can be said of the current state of research: do participatory processes facilitate social learning?
b. Which definition serves best to operationalize social learning?
c. Which indicators are suitable for measuring and monitoring social learning?
d. Are there methods to measure these indicators? If not, how could the suggested indicators be measured?
e. Which elements and processes on the individual and group level are important for social learning?
f. Which processes and factors account for the fostering or hampering of social learning during the use of participatory methods?

RQ2: How can social learning processes facilitated through participatory methods be reproduced in an agent-based model to gain a deeper understanding of involved processes and feedback?

To model how social learning can be facilitated during the application of participatory methods, it is important to identify a reasonable scope of analysis by determining the system boundaries. This is done on the basis of the literature review presented in Chapter 2. Furthermore, the model structure and important elements and processes of social learning processes facilitated through participatory methods, need to be identified. For this, I use the framework developed in Paper I and adapt it to the modeling needs in Papers III and IV. Lastly, the model should be compared to the empirical evidence to validate its soundness. This task is described in Paper IV, and partly in Paper III. RQ2 can be split up into the following sub-questions:

a. What are reasonable system boundaries for such a model?
b. Which model structure and which concepts (elements, interactions, learning processes) are appropriate for modeling social learning processes facilitated through participatory methods?
c. Is it possible to generate group phenomena?

RQ3: Is it possible to identify factors or processes that hamper/ foster social learning in participatory methods through model exploration?

RQ3 aims at an evaluation of model results and the interpretation of findings in comparison to the reality. This is done on the basis of the model results presented in Papers III and IV, and can be divided into the following two sub-questions:

    a. What can be learned from model exploration?
    b. Which questions or possible suggestions can be attributed to empirical research and participatory practice?

1.2 THESIS OUTLINE

This thesis is written as the unified work comprising the current framing document, and four research articles which are presented in Chapter 4 to 7.

The next chapter of the framing document, Chapter 2, provides an overview of the conceptual foundation and the theoretical background this thesis builds upon. It therefore embraces a literature review of relevant fields, including research on social learning, participation and group processes, a short introduction to exploratory agent-based modeling, and concepts which are useful for modeling group interaction. Each of these topics is discussed in a separate section. Research gaps are identified. Every section ends with a spotlight on the contribution that this thesis is making.

Chapter 3 presents the methodologies I apply in this thesis. Based on the results of a literature review summarized in Chapter 2, I operationalize social learning facilitated through participatory methods in a framework and identify indicators to measure whether social learning took place. To complement methods for measuring the proposed indicators, I take up and combine methods from a different area in a new way. This endeavor is described in Section 3.1. Chapter 3 ends with a documentation of how the agent-based model was built, describing all steps from a conceptual model to the evaluation of results.

In Chapter 4 to 7 the corresponding research articles are presented. First, Paper I describes an analytical framework of social learning facilitated through participatory methods, and suggests an amendment to the definition of social learning as proposed by Reed et al. (2010) (Chapter 4). Paper II then introduces a method to analyze how far individual models of various actors are merged into a joint group model, which allows for an evaluation of group model building exercises regarding the dominance of participants and the occurrence of new concepts (Chapter 5). This method can be used to measure one of the indicators suggested in Paper I. Papers III and IV describe the agent-based model CollAct, as well as the main findings gained through the simulations conducted with CollAct with respect to group dynamics (Chapter 6 and 7). Papers corresponding to his thesis include:

Paper I: Scholz, G., Dewulf, A., & Pahl-Wostl, C. (2014). An analytical framework of social learning facilitated by participatory methods. *Systemic Practice and Action Research*, 27(6), 575-591. DOI:10.1007/s11213-013-9310-z

Paper II: Scholz, G., Austermann, M., Kaldrack, K., & Pahl-Wostl, C. (2015). Evaluating group model building exercises: a method for comparing externalized mental models and group models. *System Dynamics Review*, 31(1-2), 28-45. DOI: 10.1002/sdr.1538

Paper III: Scholz, G., Pahl-Wostl, C., & Dewulf, A. (2014). An Agent-Based Model of Consensus Building. In *Social Simulation Conference*. DDD repository: http://ddd.uab.cat/record/125597

Paper IV: Scholz, G., Dewulf, A., & Pahl-Wostl, C. Social learning in an agent-based model: Using cognitive biases to simulate learning and consensus finding in group discussions. Working paper

The four papers complement each other as described in the following. The framework developed in Paper I presents an abstract conceptual model of social learning facilitated through participatory methods. Furthermore it proposes indicators to measure whether or not social learning occurred, and recommends methods to measure these indicators. As a result, I noticed a research gap because methods for comparing externalized individual mental models and a group model were missing. These are developed and tested in Paper II. CollAct, described in Papers III and IV, is developed upon the basis of the framework developed in Paper I. Furthermore, I used the indicators proposed in Paper I and the methods developed in Paper II to specify indicators that aid in evaluating the model output. The interrelationships of the papers are illustrated in Figure 1.

Finally, Chapter 8 presents the conclusions of this thesis. It starts with a critical discussion of my approach. Subsequently, I address the aim of this thesis by answering the research questions introduced above. Chapter 8 ends with an outlook on further research potential.
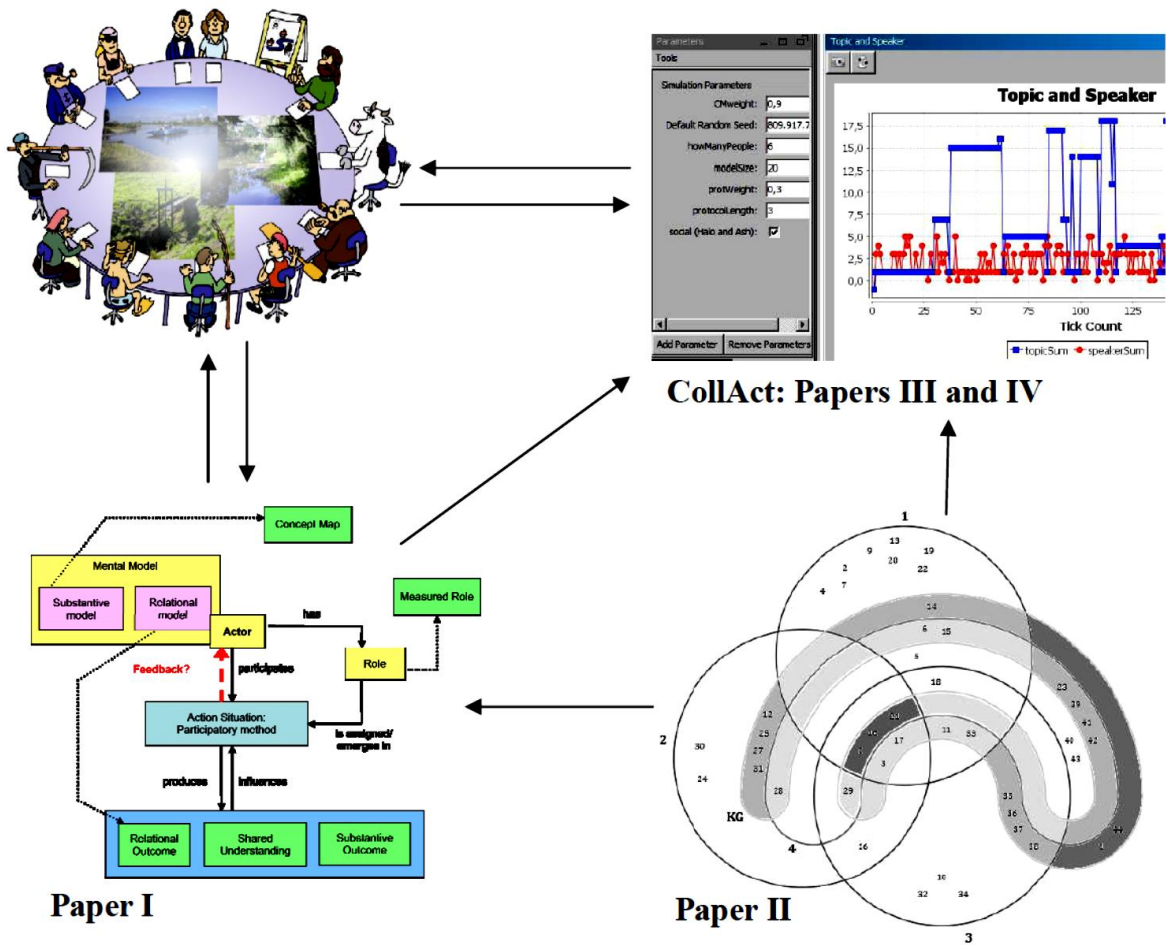
Fig. 1: Interrelationships of the papers that are part of this thesis and the focus of the research. The framework developed in Paper I and measures developed in Paper II are used to specify and evaluate CollAct (the figure on the upper left is from M. Fredrich in Ridder, Cernesson, & HarmoniCOP, 2006, p.1).

2 CONCEPTUAL AND THEORETICAL FOUNDATION

This chapter delineates the conceptual foundation and theoretical background of this thesis, and is based on a literature review of the relevant fields. It starts with an overview of social learning theories used in natural resource management, a definition, possible indicators, and open questions. Next, participatory methods that are supposed to facilitate social learning are discussed, focusing on active participation, available methods, factors fostering or hampering social learning during participatory methods, and controversial points. The third part of this section is dedicated to agent-based modeling as a method for integrating disciplinary concepts and, especially, as a tool for theoretical exploration. Subsequently, concepts used to describe and model social learning within the scope of this thesis are discussed and ranked within previously proposed scales. All sections of Chapter 2 end with a summary of the research gap addressed in this thesis.

2.1 SOCIAL LEARNING IN NATURAL RESOURCE MANAGEMENT

Learning, especially social learning is frequently regarded as an adequate strategy to confront growing complexity and uncertainty and to promote sustainable natural resource management (e.g., Muro & Jeffrey, 2008; Pahl-Wostl et al., 2008; Reed et al., 2010).

According to Carl Folke, learning in general can be defined as

> "[…] a process of change in the way we look upon the world – our thoughts, feelings and actions – which is dependent on the learner, the object of learning, and the physical, biological, social, cultural, and economic situation and setting."(Swartling et al., 2011, p. iii)

Thus, what are the features that turn learning processes into 'social learning'? Muro and Jeffrey state that

> "[…][w]hilst many social-psychological models adopt an individual based perspective on human behavioural development […], social learning theory adopts a more dynamic view that emphasises the interaction between individuals and their environment"(Muro & Jeffrey, 2008, p. 327).

In the following section I provide a short overview of social learning theories, focusing on ideas used in natural resources management, and discuss a definition appropriate for measuring social learning via indicators. Next, I provide an overview of indicators for social learning and discuss factors that may hamper or foster social learning. The section closes with a short discussion of research gaps addressed in this thesis.

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2.1.1 An overview of social learning theories used in natural resources management

The term social learning was coined by Albert Bandura (1977), who proposed a theory of learning via the imitation of others, emphasizing the interaction between individuals and their social environment. Since then, the idea of social learning has frequently been picked up and further developed (Muro & Jeffrey, 2008).

In organizational research, social learning has received considerable attention (Dodgson, 1993). As a consequence, the interactive and participative character of learning processes was reflected in the concept of *communities of practice* (Lave & Wenger, 1991; Wenger, 2000; Wenger, 1998). Another concept strongly observed across disciplinary borders was *learning organizations* (Senge, 1990), describing how organizations become adaptable and therefore able to respond to changes. In the field of social cognition theory, Salomon (1993) coined the concept of *distributed cognition* and described how knowledge is socially constructed during collaboration. The main statements of these strands of research are the situated, interactional, and context-dependent nature of learning processes (Senge, 1990; Lave & Wenger, 1991; Salomon, 1993; Muro & Jeffrey, 2008). Additionally, these theories focus more on changes in attitudes and beliefs and generating knowledge rather than emphasizing behavioral changes as classical social learning theories do (Muro & Jeffrey, 2008).

Another important aspect is the quality or depth of possible learning. This has also been addressed in organizational research, where Argyris and Schön (1978) introduced the famous concept of double-loop learning. Based on this classification of learning processes, Hargrove (1996) developed the more refined triple-loop learning framework.[3] Accordingly, a single-loop learning process means that established routines are improved step by step. The underlying assumptions remain unrevised. The question is whether things are done right. Double-loop learning occurs when reframing happens, i.e. the underlying assumptions and consequently the rules for decision making change. It is questioned whether the right things are done. Triple-loop learning occurs if a transformation of the context of the whole process or of the personal point of view takes place, involving a change in deeply rooted beliefs and values or principles. The process of determining what is right is questioned in this case. Figure 2 depicts an interpretation of the triple-loop learning concept from Pahl-Wostl (2009).

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[3] Another conceptualization of triple-loop learning, adding the dimension of reflection for managing diversity, has been developed by Flood and Romm (1996). An overview of different conceptualizations of triple-loop learning is provided by Tosey et al. (2012).
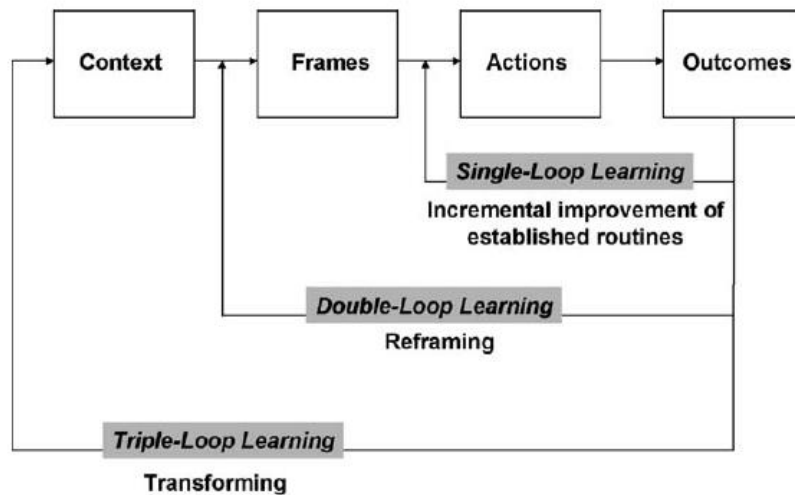
Fig. 2: Learning cycles in the concept of triple-loop learning (Pahl-Wostl, 2009, p.359, based on Hargrove, 2002)

In environmental management, e.g., natural resources management, social learning is increasingly seen as a facilitating framework and participatory approach, useful for "managing environmental problems within a larger social context" (Stringer et al., 2006, p.2). The use of social learning to support participatory planning has been especially emphasized (Muro & Jeffrey, 2008). This use of social learning theories is ambivalent, because on the one hand, participatory processes are seen as a means of facilitating social learning, while on the other, social learning is employed as a facilitating framework for participatory planning (Muro & Jeffrey, 2008). This may lead to confusion and increase the difficulty of measuring whether social learning occurred, or identifying the fostering or hampering factors for social learning.

Scholars in natural resource management who address social learning build on a variety of different theories and models; the main strands being the ones described above. Thereby, ideas from diverse disciplinary research areas influence the discourse. Rodela (2013) conducted a survey of ninety-seven studies on social learning in natural resource management. She concludes that policy studies, research on human learning and systems science have had a strong impact on the recent discourse on social learning in natural resource management. Furthermore, she found that the research on social learning is issue-driven (some geographical areas and types of resources prevail) (Rodela, 2013).

2.1.2 A definition for social learning in natural resource management

A commonly agreed upon definition of social learning as well as a shared understanding of processes it entails is still absent (Muro & Jeffrey, 2008; Reed et al., 2010; Rodela, 2013). In a report on action research Brown defines social learning as "the emergence of frames and perspectives that can reshape behaviour"(Brown, 1998, p.2). Pahl-Wostl et al. (2008) claim that

social learning also involves new relational capacities between social agents, including improved collaboration and a novel understanding of each other's capacities and roles. New framings of the issue at stake are considered to be essential. Muro and Jeffrey state that a common understanding that emerges from the literature in the field of natural resource management is

> "*that the generation of new knowledge, the acquisition of technical and social skills as well as the development of trust and relationships may form the basis for a common understanding of the system or problem at hand, agreement and collective actio*n" (Muro & Jeffrey, 2008, p.330, and references therein).

Definitions of learning often include behavioral change. Nevertheless, cognitive learning does not necessarily lead towards behavioral change (e.g., Ajzen & Fishbein, 1980). In this thesis learning is conceptualized separately from behavioral change, which may be induced through learning. Regarding the aim of this thesis, a definition that enables the formalization and operationalization of social learning is required. The definition I use throughout my thesis stems from Reed et al. (2010), providing a good basis for operationalization and measurement:

> "*[T]o be considered 'social learning,' a process must:*
> *(1) demonstrate that a change in understanding has taken place in the individuals involved;*
> *(2) demonstrate that this change goes beyond the individual and becomes situated within wider social units or communities of practice; and*
> *(3) occur through social interactions and processes between actors within a social network*".(Reed et al., 2010, p.1)

Although already widely cited this definition has some weak points. It does not address whether or not stakeholders learning together reach a shared understanding. Although there might be some learning taking place, positions can harden on both sides and the common ground may decrease. In Paper I (Chapter 4), I address this issue by suggesting adding the direction of learning, i.e., either convergent or divergent. The possibility of convergent and divergent learning has been discussed as well by van Mierlo (2012) for four case studies on niche development involving photovoltaics. She found that both types of learning may coexist and can be useful for different purposes: divergent learning for opening up the novelty's interpretation and convergent learning for the closing of it. Furthermore, she came to the conclusion that both types of learning seem to be related to different process conditions (van Mierlo, 2012).

2.1.3 Indicators - how to know if social learning occurred

To evaluate and compare different processes in the light of their social learning success, indicators are needed to judge whether and to what extent social learning took place. Each of the various definitions results in different indicators being chosen to report if social learning took place during participatory processes. Muro and Jeffrey (2008) list eight studies of social learning in participatory processes, together with the respective components/dimensions of social learning that have been evaluated. Evaluated components can be summarized as:

1. The features/methods of the exercise;
2. Learning about (i) (collective) values and preferences, (ii) impressions and feelings of others, and (iii) the management situation/the problem at stake;
3. Moral development and self-confidence;
4. Learning to collaborate and patterns of communication;
5. Relationships and trust;
6. Interrelationship between local and external knowledge;
7. Collective cognitive agency, shared values, and the identification of a common purpose;
8. Structural change;
9. Revision of norms, rules, and responsibilities; and
10. Improved management.

These criteria for evaluation relate to different time scales and levels of learning. To learn new facts requires less time and effort than to revise responsibilities and improve management. Therefore, I have arranged the ten criteria in an ascending order according to time and effort required. Furthermore, it appears mostly as if no preset indicators exist to judge whether social learning took place or not. This may be problematic when one wants to compare diverse studies to identify patterns for successful processes.

Given that evaluated components relate to different time scales and levels of learning, I further examined common ways to identify components that belong to social learning. Common divisions for the evaluation of participatory processes with regard to social learning include the categories cognitive, moral, and relational. Examples in the literature include cognitive enhancement and moral development (Webler et al., 1995), soft relational vs hard factual aspects (Pahl-Wostl & Hare, 2004), cognitive learning, normative learning, and relational learning (Haug et al., 2011), and the assessment of cognitive learning by Raadgever (2009). Quantitative measures often focus on the evaluation of cognitive learning (e.g., Raadgever, 2009; van der Wal et al., 2014). Another common classification distinguishes between different levels of social learning while evaluating the results, thus presenting indicators for social learning at a certain level (Newig et al., 2010; Pahl-Wostl, 2009). For example, Newig et al. (2010) distinguish single- and double-loop learning as well as individual and collective learning, and Pahl-Wostl (2009) characterizes changes in governance regimes expected for single-, double-, and triple-

loop learning. These possible dimensions and components of social learning should be kept in mind when identifying indicators to measure whether or not it occurred.

Regarding indicators and measures, a couple of interesting approaches have been published in the last five years. A quantitative measure that has recently been used to evaluate social learning is change in mental models (Haug et al., 2011; Mathevet et al., 2011). Mental models refer to personal internal representations of the surrounding world. Mathevet et al. (2011) measured the degree to which members of a water board share mental models by using cultural consensus analysis. Van der Wal et al. (2014) present another approach, using a comparison of perspectives derived from cultural theory and change therein to measure social learning. They use a definition of social learning from De Kraker et al. (2011) focusing on the convergent change in stakeholders' perspectives. Although promising, this approach has two limitations: first, the social-relational dimensions of learning (e.g., trust and the establishment of good relations) are not captured by the approach and, second, the perspectives derived from cultural theory are fixed, which leads to a loss of flexibility (van der Wal et al., 2014). More flexible but still limited to concepts developed at the beginning of the observed case study is the Q-sorting method, which has been applied by Raadgever to assess changes in the perspectives of participants due to collaboration (Raadgever, 2009). Another important aspect of these approaches which should be considered is that the quantitative differences of variables are difficult to measure in a reproducible and reliable fashion (e.g., mental models).

In Paper I (Chapter 4) of this thesis I propose indicators for social learning facilitated during participatory methods which also show whether the learning leads in a convergent direction. The proposed indicators denote double-loop learning as well as cognitive and relational learning.

2.1.4 Conditions that foster/hamper social learning

In the literature, an overview of influences fostering social learning can be found. These influences stem from context as well as from process features. Because process features are of particular interest in this thesis regarding the modeling endeavor, group phenomena that may occur in and impact on participatory processes as well as on their outcomes are discussed in Section 2.2.4.

A simple overview of findings reported in the literature on participatory processes and social learning, without distinguishing context and process features, forms a preliminary foundation for this research initiative. Findings from the European project 'Harmonising Collaborative Planning' (HarmoniCOP) suggest that the key factors fostering social learning are: sufficient time provided for the process, early involvement of stakeholders, and particular care given to

process management (Tippett et al., 2005). Schusler et al. (2003) state that open communication, unrestrained thinking, constructive conflict, diverse participation, multiple sources of knowledge, a democratic structure, extended engagement, and facilitation all foster social learning. Muro and Jeffrey (2008) summarize the following process features that account for fostering social learning:

- Facilitation;
- Small group work;
- Egalitarian atmosphere;
- Repeated meetings/opportunities for interaction;
- Opportunities to influence the process;
- Open communication;
- Diverse participation;
- Unrestrained thinking; and
- Multiple sources of knowledge.

On the other hand, limited resources and time account for hindering social learning (Muro & Jeffrey, 2008). These are important restraints: especially when stakeholders across wide spatial scales should be included, this places a high demand on time and money resources (Stringer et al., 2006).

A short time period may encompass interactions in a group in specific settings while longer time periods may also include structural changes in networks and the institutionalization of results. An additional aspect of longer time scales is that previous experiences between the stakeholders influence further ones. Previous successful cooperation and the trust built facilitates further collaboration (Muro & Jeffrey, 2008). Tippet et al. (2005) also found that a prior experience with participation and cultural and institutional contexts had a strong influence on participatory processes.

Furthermore, it remains difficult to determine the conditions under which social learning facilitates collaboration, collective action, and new solutions in natural resource management (Muro & Jeffrey, 2008). To address this issue, longitudinal case studies are needed. Colvin et al. (2014) started to address this gap by reporting on three long-time case studies. One of the conclusions they came to was that building and maintaining social relations is critical for sustainable development (Colvin et al., 2014).

2.1.5 Research gap addressed in this thesis

To answer the question if social learning occurred, it is necessary to discuss *what* exactly social learning is. However, a commonly agreed upon definition for social learning as well as a shared

understanding of entailed processes is still missing (Muro & Jeffrey, 2008; Reed et al., 2010; Rodela, 2013). Although there is a lot of activity with respect to specifying and synchronizing social learning approaches (e.g., Reed et al., 2010; Rodela, 2013), this process is still ongoing, and the widely cited definition of social learning from Reed et al. (2010) may still be improved (see Section 2.1.2). The different definitions result in different indicators chosen to reveal if social learning took place. As a result, the most recent approaches to measuring social learning focus on cognitive learning while neglecting the social-relational dimensions of learning[4]. This is a challenge for future research because relational aspects are an important element of most conceptualizations of social learning, including issues like trust and the building of relationships.

As a part of this thesis, I suggest an amendment in Paper I (Chapter 4) to the definition from Reed et al. (2010). This amendment addresses the issue of whether or not stakeholders learning together reach a shared understanding by adding the direction of learning, being either convergent or divergent. Furthermore, Paper I provides an analytical framework and indicators to measure whether social learning occurred in small groups interacting within the scope of participatory methods. These indicators take cognitive and relational learning into account and can be used to denote at least double-loop learning. Paper II (Chapter 5) supplements methods to accomplish the respective measurements. The proposed method can be used to determine the dominance of participants and if new concepts emerged from the process.

2.2 PARTICIPATORY METHODS AS A MEANS OF FACILITATING SOCIAL LEARNING IN NATURAL RESOURCE MANAGEMENT

Participatory approaches have become increasingly popular in governmental policies and ecosystem management (Folke et al., 2005). In natural resource management, the participation of the public plays an ever more central role (Schusler et al., 2003). Social learning is an important aspect of participatory processes, e.g., in water management (Pahl-Wostl et al., 2007). Participation is a possible way of triggering learning processes (Webler et al., 1995). Since 2000, social learning has especially been promoted as a way to support participatory planning (e.g., in water management, forest management, conservation planning, and participatory rural research) (Muro & Jeffrey, 2008). Again, this is an ambiguous conceptualization, because on the one hand social learning is employed as a facilitating framework for participatory planning (taking a rather normative perspective), while on the other, participation is expected to facilitate social learning. The direction of the causality is not clear, and when social learning is used as framework for a participatory endeavor it is rather difficult, or at least biased, to evaluate whether participation facilitates social learning. However, even if social learning is taken as a

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[4] Haug et al. (2011) also report on relational and normative learning.

conceptual framework to design a participatory endeavor, this does not mean that social learning as a process with a measurable outcome actually occurs in this endeavor. Thus, it may still be useful to evaluate whether or not social learning took place.

In the following, the scope and goals of participatory processes focused on in this thesis are discussed. Participatory methods applied in such processes are introduced, followed by a discussion of the extent to which participatory processes facilitate social learning, and then a discussion of the importance of group interaction and process features. At the end of this section, I summarize the contribution of this thesis related to these issues.

2.2.1 Participation in natural resource management: Scope and goals

Most decisions in natural resource management do not only affect decision makers, but diverse stakeholders[5] with differing perspectives. In participatory processes these perspectives can be appreciated and a shared problem perception and an acceptable solution may possibly be reached. However, while the expected benefits of participation have influenced its incorporation into policy and international declarations (Mostert, 2003; Reed, 2008), disillusionment has been growing amongst practitioners and the involved public in cases where the promoted benefits could not be realised (Reed, 2008). There is an ongoing discussion about the effects of participation, including its effects on social learning (e.g., Cooke & Kothari, 2001; Kesby, 2005; Reed, 2008).

Expected benefits from participation can be broadly divided into normative and pragmatic aspects (Reed, 2008). Normative aspects include expected benefits for citizenship, equity, and democratic society, while pragmatic aspects concentrate on the quality and durability of achieved decisions (Reed, 2008). While the facilitation of social learning through participation can be seen as a normative benefit (e.g., be Reed, 2008), it can as well support pragmatic claims. During participatory processes, implicit assumptions may become visible, which helps in the discovery of acceptable solutions for all involved actors (Tippett et al., 2005). Through fostering communication and learning, it can be possible to reach consensus and arrive at a decision (Stringer et al., 2006). Mostert (2003) provides an overview of the potential benefits and problems of public participation, displayed in Table 1.

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[5] Stakeholders can be defined as "those who are affected by or can affect a decision" (Reed, 2008, p. 2418, based on Freeman, 1984).

Table 1: Potential benefits and problems of public participation (Mostert, 2003, p.181)

Potential Benefits	Potential Problems
Better-informed and more creative decision-making	Reluctant government that gives no serious follow-up, resulting in disappointment and *less* public acceptance of decisions
Greater acceptance of decisions, fewer implementation problems	
Social learning of all involved	Limited and unrepresentative response
More open and "integrated" government	Low-quality response
Enhanced democracy	Inconsistent decision-making
Environmentally and economically sustainable water management	Costs and time

Several classifications for participatory processes exist, e.g., distinguishing objectives, the degree of participation, structure, function, or the direction of information flow (Reed, 2008; Stringer et al., 2006). For this thesis the level of interaction is of particular interest. Stringer et al. (2006) propose a classification of public engagement based on Rowe and Frewer (2005), differentiating between public communication, public consultation, and public participation. Thereby, public communication and public consultation describe processes with one-way information flow (the initiative's sponsor either informs the public or collects information from the public), while in public participation a two-way information flow in form of a dialogue takes place, often in an iterative or cyclical way. As a result, public participation is characterized by active involvement in interactive settings, especially in group settings. The process characteristics discussed in this thesis and the related agent-based model are especially important for the third type, public participation, incorporating group interaction. I therefore use participation as a term for active involvement, and do not consider public communication and public consultation in more detail.

There are various suggestions for improving participation. These include frameworks for when to use which methods at various stages within a participatory process (e.g., Krywkow, 2009; Mostert, 2003). Other voices plead for a more flexible approach, focused around context and process needs. Based on a literature review, Reed (2008) has summarized eight key features for successful participation:

- A philosophy that emphasizes empowerment, equity, trust and learning;
- Participation as early as possible and throughout the whole process;
- Analyzing and representing relevant stakeholders systematically;
- Agreement upon clear objectives among the stakeholders from the outset;
- Selection and adaption of methods according to the decision-making context;
- Highly skilled facilitation;
- Integration of local and scientific knowledge; and
- The institutionalization of stakeholder participation.

Public participation is not a panacea for all problems; it can as well be problematic by incurring social and economic costs, and may not even be effective (Irvin & Stansbury, 2004). Irvin and Stansbury (2004) provide a list of factors to aid the decision of whether or not participation is a good choice for a specific situation, categorized by low-cost versus high-cost and high-benefit versus low-benefit indicators. To estimate the costs, the important factors are whether or not citizens readily volunteer, how large the geographic area in question is, whether potential participants need financial support to attend meetings, and whether or not the issue at stake requires mastering complex technical information. Furthermore, homogenous and smaller groups may speed up decision processes. To estimate the potential benefit from participation, additional indicators are used: A gridlocked issue is a reason to involve stakeholders. Further aspects that should be considered are whether or not the public is hostile towards the responsible government entities, if influential representatives are willing to participate, if the facilitator has credibility among all participants, and if the issue is of high interest to stakeholders (Irvin & Stansbury, 2004).

2.2.2 Participatory methods

To support participatory processes, various methods are available. Participatory methods dealt with in this thesis can be defined as

> *"methods to structure group processes in which non-experts play an active role in order to articulate their knowledge, values and preferences"* (van Asselt & Rijkens-Klomp, 2002, p. 168).

Such methods can be applied to help participants to become aware of and to respect different viewpoints (Tippett et al., 2005). Thereby, the applied methods should be adapted to the particular decision-making context (Reed, 2008). Mostert (2003) proposes a scale that is ranging from 'information' to 'decision making' of stakeholders. On 'lower' levels, there is only a one-way information flow (see previous section), while on 'higher' levels the institutionalization of participation is more important, e.g., the representation of the public in governing bodies. The focus of this thesis on group processes (implying group interaction) is thus most relevant to the mid-level: discussions and possibly of co-designing or co-decision making. For these, Mostert (2003) proposes small group meetings (e.g., workshops, round tables, brainstorm sessions, citizen juries, focus groups), large group meetings (involving the splitting of large groups into smaller ones and rotate group division), negotiation, and the representation of the public in

governing bodies[6]. The focus in this thesis is on group methods embracing and fostering discussion, and particularly on methods applied in smaller groups, i.e., small group meetings and negotiations.

Participatory methods can provide room for social learning by fostering constructive dialogue and the building of mutual understanding. This does not necessarily include consensus, but at least an awareness of divergent opinions and arguments. Van Asselt and Rijkens-Klomp (2002) provide a summary and comparison of participatory methods applied over various disciplines. They propose a classification of participatory methods based on two scales, concerning the original rationale and the way the methods are generally applied. The first scale extends from 'mapping out diversity', which is about collecting ideas and information, to 'reaching consensus'. The second scale indicates whether or not the process of participation is seen as a goal in itself (empowering stakeholders and strengthening democracy). Figure 3 displays the classification from van Asselt and Rijkens-Klomp (2002).
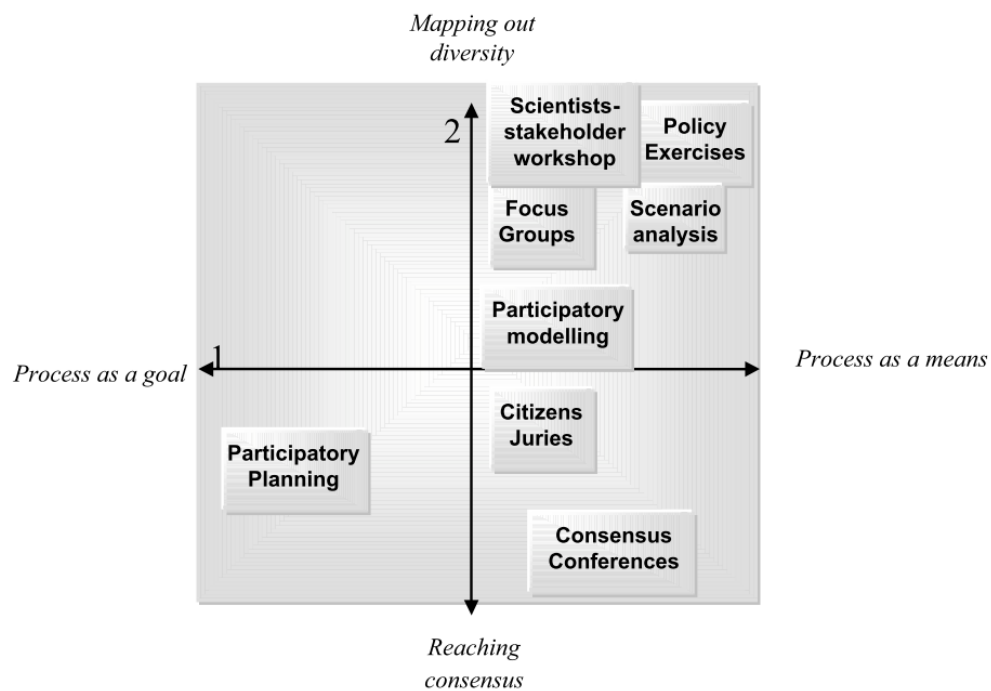
Fig. 3: Typology of goals of participation: (1) aspiration/motivation axis (2) targeted output axis (van Asselt & Rijkens-Klomp, 2002, p.169)

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[6] For a framework suggesting when to imply which method see, e.g., Krywkow (2009), and for a description of participatory methods van Asselt and Rijkens-Klomp (2002).

As an illustrative example of participatory methods, I describe group model building (or participatory modeling) in more detail in the following section. For group model building, an overview and analysis of case study literature is provided in Rouwette et al. (2002), which includes aspects of social learning. Furthermore, the conceptualization of a group model building exercise served as foundation for the agent-based model CollAct, which I develop within the scope of this thesis.

Group Model Building

Group model building is a method that can, in addition to providing a (conceptual) model, enhance team learning (Rouwette et al., 2002). The goal of a group model building process is to develop a joint model which is approved by all participants. It can be used to tackle complex and 'messy' problems, i.e. situations where people hold dissimilar views about the existence and type of the problem (Vennix, 1996). In group model building processes, stakeholders jointly develop a model of the problem at hand (Andersen & Richardson, 1997; Vennix, 1996). As stakeholders have different backgrounds, multiple perspectives are included. An additional goal is the development of a shared understanding of a problem, thereby facilitating joint action (Vennix, 1996). Group model building processes are normally facilitated by an expert who understands the subject matter and has experience in effectively moderating such exercises. To develop a conceptual model, graphical tools are used, e.g., concept maps and causal loop diagrams. Concept maps are diagrams that graphically display concepts and the (directional) relationships between these concepts. In causal loop diagrams variables (concepts) are linked by positively (enforcing) or negatively (decreasing) labelled links. Two or more links can result in a loop which may be reinforcing or balancing in general. Figure 4 depicts such a model developed during a group model building process in Cyprus.
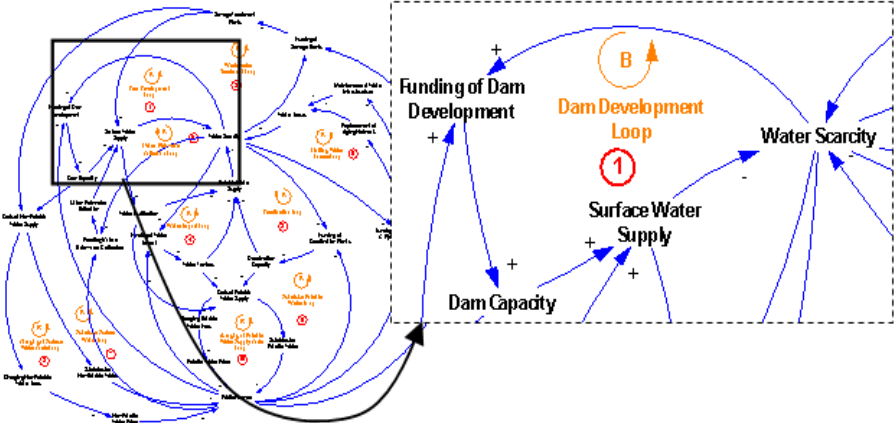
Fig. 4: Example of a Causal Loop Diagram of water scarcity in Cyprus based upon Halbe (2009, Appendix B1)

The following are expected results from group model building processes including (after Rouwette et al. (2002), p.9-10, adjusted to group model building processes in the context of resource management):
- At the individual level:
  o Reactions to the model and intervention;
  o Learning (insight);
  o Commitment to results; and
  o Changes in behaviour.
- At the group level:
  o Better exchange of viewpoints;
  o Shared view of the problem; and
  o Shared language / understanding of other participants.
- At the organizational/societal level:
  o System changes and the consequences of these changes.

Rouwette et al. (2002) compared 107 group model building cases from the literature. Of the 101 that reported on the learning process, 96 cases indicated an increase in insight among participants (Rouwette et al., 2002, p.16). This lead to the conclusion that group model building generally results in increases in insight. Additionally, 41 cases reported on communication, 40 of which indicated an increase in the quality of communication. Of the 53 cases reporting on consensus building, 49 cases had successfully created consensus (Rouwette et al., 2002).

Another reason to choose group model building lies in its potential for evaluation, which is explored in Paper II (Chapter 5). It is possible to externalize individual mental models through concept mapping prior to the group model building process[7]. These concept maps can be compared with the resulting group model to evaluate how far individual models merged into the group model. Methods to accomplish this task are developed and tested in Paper II of this thesis.

2.2.3 Effects of participation on social learning

What conclusions concerning the effects of participation with respect to social learning can be drawn? Mostert (2003) states that public participation can promote social learning if all parties take part in a constructive dialogue. Muro and Jeffrey (2008) report positive, mainly social-relational outcomes found in the literature on participatory processes linked to social learning: an increased understanding of resource management, increased understanding among participants of their respective roles, discovery of areas of agreement and disagreement, identification

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[7] Because mental models exist within the minds of individuals, they cannot be analyzed directly, and only be externalized with limitations (see also Papers I and II, and the discussion in Chapter 8).

of a common purpose for future efforts, and several types of individual transformations (e.g., increased confidence in own skills). Stringer et al. (2006) report on social learning as an outcome of participatory processes, including new knowledge and a collective understanding. Nevertheless, positive empirical evidence that participatory methods foster social learning is still rare. Reed (2008) states that there is little evidence supporting the claim that stakeholder participation enhances social learning, partly as a result of the lack of methods for measuring social learning.

Very recently, some efforts to quantify social learning have been made, most of them focusing on the evaluation of cognitive learning (Haug et al., 2011; Mathevet et al., 2011; Raadgever, 2009; van der Wal et al., 2014). Thereby changes in externalized mental models (Haug et al., 2011; Mathevet et al., 2011) and perspectives (Raadgever, 2009; van der Wal et al., 2014) of stakeholders were quantified and evaluated. Most of these studies conclude that learning occurred (Haug et al., 2011; Mathevet et al., 2011; van der Wal et al., 2014), while Raadgever (2009) finds that only intense collaboration enhances learning. This can be seen as being consistent with the other findings: for the evaluation of a single policy exercise only limited learning is reported (Haug et al., 2011), while for the membership of a Water Board learning occurred, resulting in richer mental models as well as in an increased overlap of mental models of group members (Mathevet et al., 2011).

Hence, empirical findings suggest that participatory processes may enhance social learning. However, all recent case study findings cited here use different methods to measure whether or not learning occurred (even if they evaluate similar concepts). Furthermore, various settings were evaluated[8]. Therefore, the findings highlight different aspects of social learning. Thus, further research in this area is needed in order to compare data.

2.2.4 Group interaction and social processes

> *"What is it about "social learning" that attracts such an interesting diversity of scholars in the field of natural resource management and resilience? I think an important part of the answer has to deal with an increased interest in not only the structures of adaptive governance - i.e. institutions and networks - but also in the social processes that are truly able to bring to light the ability of people to collaborate, share insights, build common understandings and promote positive change."* (Victor Galaz in Swartling et al., 2011, p.iii)

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[8] The settings evaluated varied between a policy exercise (Haug et al., 2011), participatory processes in water and land management (Raadgever, 2009; van der Wal et al., 2014), and learning in a Water Board (Mathevet et al., 2011).

Both context and process conditions are important for the results of participatory processes and the type of learning which may occur (Stringer et al., 2006; van Mierlo, 2012). Koontz (2013) finds that higher levels of process control and individual efficacy lead to higher levels of social learning. Sol et al. (2013) describe trust, commitment and reframing as emergent and interrelated aspects, that occur in the process of social learning and influence each other and the further process. The process in participatory methods is found to be probably even more important than the specific methods chosen (Reed, 2008). However, only little knowledge exists about the social dynamics in the process of social learning (Sol et al., 2013). These findings corroborate the importance of taking a look 'inside' participatory processes: what can be said about the dynamics which may occur through group interaction during the employment of participatory methods?

As discussed above (see Section 2.2.2), the focus in this thesis is participatory methods that embrace and foster discussion, and particularly on methods applied in smaller groups[9]. Within the groups organized for the purpose of participation, certain dynamics can occur which do not have to be positive. In the context of participatory development, Cooke (2001) reviews the social-psychological limits of participation, and lists four different problematic dynamics which may occur: risky shift, the Abilene paradox, groupthink, and coercive persuasion. Cooke (2001) focuses on participatory development; nevertheless, these issues are worthy of investigation with regard to participatory processes in general. A risky shift describes the tendency of groups to produce significantly more risky decisions than individuals would (Stoner, 1968). The Abilene paradox refers to the inability to manage agreement: When all participants accept and support what they believe the others want, this can end in a situation that nobody wants (believing all others would want it) (Harvey, 1988). The theory of group think was proposed by Janis (1972), and describes the dynamics in cohesive decision-making groups, which lead to a consensus at any cost, excluding doubts and other opinions. This can lead to obviously wrong or bad decisions (for outsiders). Finally, coercive persuasion provides a conceptual explanation of mechanisms which could best be described as a sort of 'brainwashing' (for further explanation see Cooke, 1998). Two symptoms that are common to both group think and the Abilene paradox are self-censorship (participants keep silent even if they have doubts or disagreements) and the feeling of unanimity within the group (silence is interpreted as concurrence with the view of the majority) (Cooke, 2001).

Conformity is an important driver for group dynamics. Conformity refers to cases where participants try to align to some social norm, or the (supposed) 'group opinion'. Conformity can have two causes: First, fear of punishment or rejection, and second, trust in others' opinions –

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[9] Groups can be defined as "two or more interdependent individuals who influence each other through social interaction" (Forsyth, 1999, p.5, cited after Baron & Kerr, 2003).

especially those based on group consensus (Baron & Kerr, 2003). While conformity can lead to irrational judgements and bad decisions, it also provides some benefits: Often the heuristic conclusion that the majority is right is justified, and furthermore, conformity increases the likelihood that participants consider group interests (Baron & Kerr, 2003). This last point might especially be interesting for participatory processes.

Another sensitive issue that may have negative impacts on group processes and the outcomes of participatory methods are power relations (Muro & Jeffrey, 2008). Stringer et al. (2006) note the risk of problems for minorities in expressing their perspectives, leading to an initial lack of engagement in one of their case studies. Power relations are not only linked to certain participants or central sites, but run through the whole social body, expressed through a variety of cultural behaviors and normalization (Kothari, 2001). Furthermore, the production and representation of knowledge cannot be separated from the exercise of power (Kothari, 2001).

Considering the pitfalls which may arise through group dynamics, facilitation of the process is seen to be even more important. If power dynamics are problematic, special care may be needed to choose methods that equalize power and give weight to marginalized voices (Reed, 2008). Furthermore, selecting the 'right' stakeholders to participate is not trivial at all, and strongly related to the definition of the problem (Mostert, 2003). It is important to not only include 'the usual suspects' and thereby risk overlooking minorities; and in some cases mediating actors, accepted by all participating stakeholders, may be needed for a successful process (Stringer et al., 2006).

In summary, it is important to consider social processes and dynamics that take place during face-to-face group interaction in order to analyze and model participatory methods. These processes can generate desired outcomes such as trust (Sol et al., 2013), but also lead to unwanted group dynamics (Cooke, 2001). While analyzing group interaction, two important features to consider are the tendency to conform, and the influences of power relations.

2.2.5 Contribution of this thesis

The social processes occurring within participation may hamper or foster social learning in participatory settings. Little knowledge exists about the social dynamics in the process of social learning (Sol et al., 2013). Thus, investigating group interaction and resulting dynamics is an important endeavor for a better understanding of social learning. The focus in this thesis is participatory methods applied in smaller groups including face-to-face group interaction. Thereby, two important features to consider are the tendency of individuals to conform to what they perceive as the views of the majority, and the influences of power relations. However, these issues are not particularly easy to investigate in empirical case studies. Agent-based models provide a good way of analyzing which combinations of theoretical assumptions lead to certain outcomes, and how different processes can influence each other (based on incorporated model assumptions). The implementation of such an agent-based model, CollAct, is part of this

thesis (Paper III and IV). CollAct considers not only cognitive but also relational learning, and includes conformity and relational influences, including power. Hence, CollAct provides a starting point for determining group interaction during social learning processes, and may help to analyze trade-offs which occur through conformity and relational influences.

Additionally, the method suggested in Paper II can be used to determine the dominance of participants in group model building exercises with respect to the resulting group model, which might be another interesting starting point for evaluating the influence of power relations.

2.3   EXPLORATORY AGENT-BASED MODELING

> *"All models are wrong but some are useful"* George Box, cited after Epstein (2008, p.4)

A model is always a mere simplification of reality, and thus wrong. A good, or as George Box puts it, 'useful' model may still serve a number of purposes, of which prediction is the most widely known. However, prediction is not the only good reason to build a model. Epstein (2008) points to 16 reasons to model besides prediction. Some of these are well within the scope of the model I develop as part of this thesis: the illumination of core dynamics, the demonstration of tradeoffs, challenging the robustness of prevailing theory, and maybe even the discovery of new questions.

To be able to develop a 'good' model, the design should be guided by the purpose. Furthermore, modeling involves at least three steps, illustrated in Figure 5: i) mapping evidence/phenomena to the model, ii) inference using the model, and iii) decoding/interpreting model results back to the observed phenomena (Edmonds, 2000).
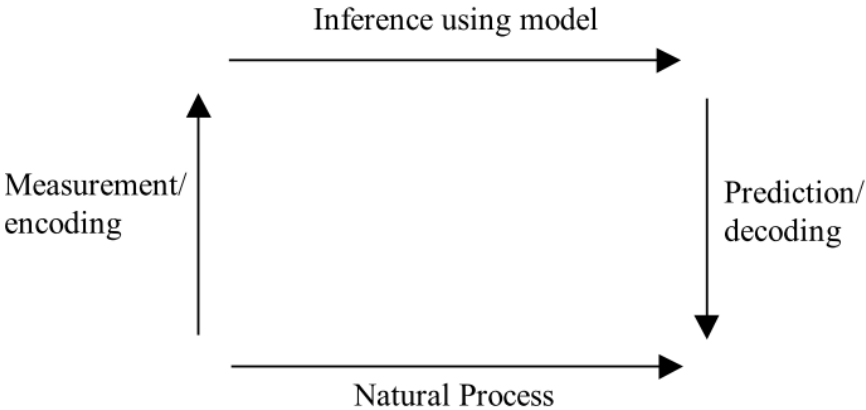
Fig. 5: The basic modeling relation (Edmonds, 2000, p. 2)

These steps apply to all kind of models (e.g., mental models and conceptual models), while computer models have another advantage: the testing and calculating of model runs is executed by the machine, allowing for far more variations than human resources could handle manually.

In the following I provide a short introduction to agent-based models. Next, I discuss the integration of different concepts during model development and exploration as the main purposes of the agent-based model developed as part of this thesis.

2.3.1 Agent-based modeling

The core element of agent-based models[10] is agents interacting with their environment in a simulation run. An agent can be defined as "[…] a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives." (Wooldridge, 1999, p. 29, adapted from Wooldridge & Jennings, 1995) Agents handle decisions via rules, which describe the agents' behavior. Agents are encapsulated in a part of the source code, the *computer system*. Agents interact with their *environment*, which includes other agents. This means they receive information from the environment and can exert influence upon their environment. Agents are capable of *autonomous action*, meaning that agents are able to decide upon further action based on information received from the environment. To achieve this, agents need devices to perceive the environment and a set of rules which determines their behavior. Finally, agents have *design objectives*, which guide their decisions. These may be fixed or variable.

What makes agent-based models interesting for social science is their ability to reproduce complex emergent patterns out of simple interactions between agents. Emergence refers to the occurrence of new behaviors or patterns at a higher level and which arise through the interaction of objects at a lower level, but which cannot be reduced to the elements on the lower level. Examples of emergent phenomena are an ant trail or the formation of a swarm of migratory birds. There is no "controlling instance" in the formation of an ant trail. It occurs through the interaction of single ants: Ant *A* is searching for food. If *A* finds food, it will leave a pheromone trace on the way back the ant pile. Other ants will follow the pheromone trace if they come across it, which leads them to the food source. On their way back to the pile the other ants reinforce *A*'s pheromone trace, and an ant trail occurs. An example for an emergent social phenomena is a norm. People might react to what they perceive to be an appropriate behavior by

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[10] Various introductions and descriptions of agent-based modelling exist. See for example Gilbert and Troitzsch (2005) for simulation within the social sciences or Woolridge et al. (2009).

observing others (also see conformity in Section 2.2.4), reinforcing this norm through their behavior (which again is observed by others).

Another characteristic of agent-based models that qualifies them for use in the social sciences is their flexibility. Humans or social entities can be modeled as agents, acting according to specified rules. These rules can encompass all kind of actions and decision structures, e.g., optimization, social-psychological theories or heuristics. The agents' environment can also be modelled in various ways, constrained only through programming languages and the modeler's creativity. However, this advantage of agent-based models also poses a serious challenge to the modeler, because every possibility of choice demands a design decision. To decide upon agents' rules is a rather delicate and not at all trivial process.

2.3.2 Integration and exploration as model purpose

The agent-based modeling exercise which is part of this thesis has two main purposes: the integration of knowledge from various strands of research, and the exploration of dynamics that may occur during the application of participatory methods.

The first purpose, the integration of knowledge, may be seen in light of the various fields of science touching on the core elements of social learning facilitated through participatory methods. Social learning receives broad attention in natural resource management and resilience research (e.g., Swartling et al., 2011), and the literature on participatory methods is represented in various disciplines (van Asselt & Rijkens-Klomp, 2002). The issue of learning in groups is addressed in team learning and small group research. Finally, group dynamics and the behavior of individuals in group settings are dealt with in social psychology. Hence, various theoretical concepts and also empirical findings do exist (see Sections 2.1, 2.2, and 2.4 for a discussion of research relevant for CollAct). A common problem in research is that disciplinary boundaries hamper the diffusion and efficient use of existing knowledge. For the modeling of a complex phenomenon like social learning through group interaction it is necessary to include theories from diverse disciplines. Furthermore, the construction of a model allows fostering a shared language by combining and formalizing knowledge across disciplinary boundaries.

The second purpose of the model CollAct, which is developed as part of this thesis, is exploration. Exploration in this context means the specification of rules at the micro level, the agents, and the identification of dynamics that occur in the model run with different parameterization. Thus, an exploration allows estimating which set of rules (theoretical assumptions) is necessary and sufficient to reproduce certain patterns. In CollAct, the concepts integrated during model building are implemented in a way that allows the on/off switching of assumptions, and the regulation of their impact. Accordingly, the consequences of different assumptions and of their dynamic interplay can be explored. Furthermore, participatory research is context-specific, which may imperil the transferability of results (Stringer et al., 2006). The huge amount of

possible parameterizations which are possible in CollAct allows the simulation of different contexts. Model outputs can then be analyzed for robust results that occur over a broad range of different parameters, correlations, and effects. These can be interpreted back to reality to aid the understanding of processes important during group discussions and help to illuminate the effects of individual properties on group dynamics.

2.4 CONCEPTS USEFUL FOR MODELING SOCIAL LEARNING FACILITATED BY PARTICIPATORY METHODS

To understand how people develop a shared understanding[11] within an interactive situation structured through a participatory method, it is important to look at interpersonal as well as socio-cognitive processes (van den Bossche et al., 2006). I treat the development of a shared understanding as an emergent outcome. The main points of interest for the model are: What happens during the building of a shared understanding, and how individuals' characteristics and group properties influence each other. The influence of individual member characteristics (e.g., mental models) on group processes is difficult to measure and analyze, and little research exists on the impact of these variables on the group process (Massey et al., 1997).

From this starting point I look at concepts useful for modeling participants' interaction within settings facilitated through participatory methods. In the first part of this section, I propose three scales on which concepts and processes can be ranked. This endeavor allows the clear separation of the micro level of implemented concepts and the macro level of emergent outcomes. Next I discuss mental models and describe mental models in more detail with respect to the proposed scales. Following this, I discuss how to model processes (learning and the interpretation of influences from the environment), and finish Chapter 2 with an illustration of my effort at producing emergent group phenomena in this thesis.

2.4.1 Discussing scales and levels

To be able to classify and discuss concepts, I use the terms scale and level as discussed by Gibson et al. (2000). Thereby scale is "[t]he spatial, temporal, quantitative, or analytical dimensions used to measure and study any phenomenon" (Gibson et al., 2000, p.218), and level refers to "[t]he units of analysis that are located at the same position on a scale […]" (Gibson et al., 2000, p.218). Levels on a scale may be ordered in a hierarchy, but this is not a necessary condition.

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[11] Shared understanding refers to convergence in the mental models of actors.

In the following, three scales relevant for social learning are identified. To discuss different scales of social learning is not a new idea. The *depth of learning* has been addressed in the double- and triple loop learning frameworks (see section 2.1.1). This discussion is picked up and turned into the first scale (depth of learning). Another scale which has been examined earlier is the *social* one (e.g., Crossan et al., 1999; Newig et al., 2010; Pahl-Wostl et al., 2007). The social scale is important because processes and products in social learning processes happen on different social levels (individuals, groups, wider social units), which may influence each other. The third scale I use is *form*. This stems from Kim (2009) who used this classification to discuss what they refer to as group processor (concepts similar to mental models at the group level). Form refers to the scale between processes and products. For example, a decision is a *product*, primarily in a rather enduring form (e.g., a management plan). On the other hand, a change in opinion may occur at various times within a discussion, being closer to the *process* end of the scale. Form is also linked to the time period that is considered. Over a long time period we may look at products, which, if we considered only a short part of this period, are composed of smaller processes. On the other hand, some 'fixed' conditions, seen as products evolving in a shorter time period, may change slowly and therefore represent a process in a longer time period. The three scales are illustrated in Figure 6.
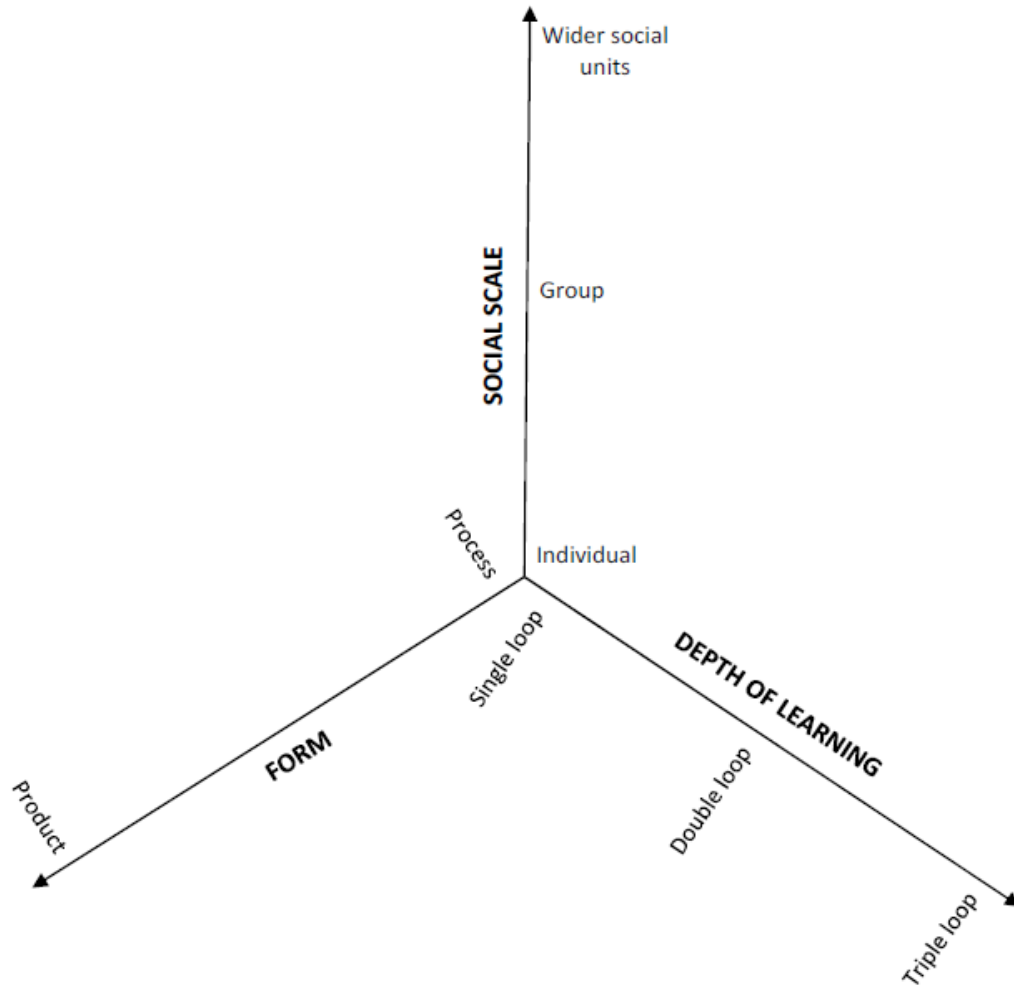
Fig. 6: The three proposed scales of social learning and their respective levels. This classification allows the separation of the micro level of implemented concepts from the macro level of emergent outcomes.

2.4.2 Mental models

A core component of my thesis is the mental model concept, referring to personal internal representations of the surrounding world. The mental model concept is the focus of growing interest in the resource management community (Lynam & Brown, 2011), and perceived to be useful for paradigm change processes (Pahl-Wostl et al., 2011). Mental models define one's relation to the environment by determining how one observes the world. They have been discussed and dealt with in many various disciplines, e.g., system dynamics, psychology, business management, learning and instruction, and interactive learning environments (Kolkman, 2005). The mental model concept partly overlaps with concepts such as cognitive schema and the cognitive frame (Dewulf et al., 2009).

Ranking the mental model concept on the three scales

In this section, mental models are discussed with respect to the three proposed scales. Mental models can be placed on different levels of the three scales, depending on their definition. In example, there are conceptualizations for 'collective mental models' on group level. In the following, I discuss each scale for the mental model concept.

Mental models and the **depth of learning**: With respect to the depth of learning, I argue that change in a mental model indicates double (or even triple) loop learning at the individual level (also see Sterman, 2000). Figure 7 illustrates this process: Mental models are the basis for criteria for decisions and actions. Actions influence the environment, which can be observed as information. If the next decisions are taken upon the same decision criteria, only single loop learning could take place. However, if the underlying mental model changes decision criteria may be revised, leading to double loop learning.
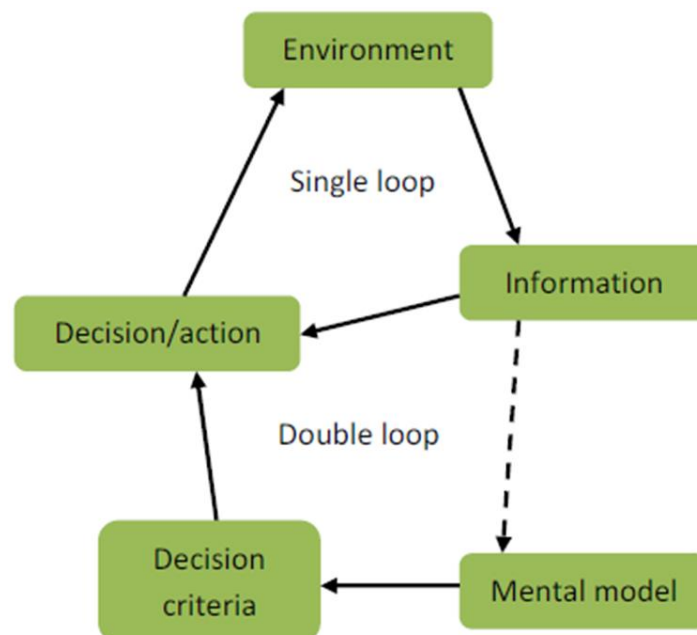
Fig. 7: Change in mental models is double loop learning (based on Sterman, 2000)

Mental models and the **social scale**: A mental model refers to an internal representation, and is therefore located at the individual level. However, at group level mental model-like concepts exist, presenting a possibility to link the individual and group level with the mental model concept. In this thesis, I use the term shared understanding for the convergence in the mental models of actors. Nevertheless, various terms (e.g., common ground, group processor, group cognition, group mental model, shared mental model, team mental model) describe collectively created

meaning, while the conceptualizations partly overlap (Akkerman et al., 2007; Kim, 2009). Mental model-like concepts at the group level differ from individual mental models because in group settings interaction and communication among individuals shape the results (e.g., group model or plans) (Kim, 2009).

Mental models and **form**: Where mental models should be placed along the 'form' scale depends on their exact definition. Following Doyle and Ford (1999, p. 414), I conceptualize mental models as "relatively enduring and accessible". Thus, I place them at a medium level in the 'form' scale. For mental model-like concepts on the group level Kim (2009) provides a classification and overview of where to place the various conceptualizations according to 'form'. Shared understanding as used in this thesis is located at a medium level, being neither 'in the process' nor a fixed product. A fixed product resulting from a participatory method that could provide insight into the amount of shared understanding at a given time is, for example, a group model resulting from a group model building process. Nevertheless, a group model is not equivalent to shared understanding, because if a compromise is included in it, this does not mean that participants' mental models actually overlap.

2.4.3 Useful theories to model learning and group interaction

Learning in mental models can be explained through a constructivist approach. In conceptual change theory (Posner et al., 1982), learning is described as an outcome of the interaction between currently held concepts and new phenomena encountered in the world. From the research on cognitive learning and mental models, I selected the following theories which are easy to implement in an agent-based model:

1. Confrontation with new knowledge can lead to a change in concepts (Anderson, 2000);
2. People develop concepts quickly on little evidence, and tend to stick to these concepts in the absence of strong evidence against them (Dörner, 1999); and
3. People tend to search for information that supports their assumptions. This phenomenon is called Confirmation Bias (Plous, 1993).

Another important task, besides providing a theoretical basis to model learning, is the inclusion of relational and cognitive knowledge and their interrelations. How can conformity and social influences in groups be modeled by making use of substantive and relational models?

People possess a number of cognitive biases. It is beyond the scope of this thesis to discuss and include all of them. However, two well-known and empirically proven cognitive biases are of specific interest for linking the knowledge represented in relational models to the perception and decision processes of agents: The Asch effect (Asch, 1951) and the halo effect (Thorndike, 1920). The Asch effect describes how people conform to obviously wrong judgments under perceived group pressure. Thus, it is useful for modeling conformity. This includes two symptoms that are described for both group think and the Abilene paradox: Self-

censorship (participants keep silent even if they have doubts or disagreements) and the feeling of unanimity within the group (silence is interpreted as concurrence with the view of the majority) (see Section 2.2.4). Both are considered in the implementation of the Asch effect within CollAct. The halo effect describes how a positive judgment of a person in one dimension (e.g., good looking) creates a positive bias in the judgment of this person in any other dimension (e.g., intelligent). The halo effect can be used to include the knowledge of the relational models of agents in the decision process. Both the Asch and halo effects can be modeled and simulated through the use of relational and substantive knowledge, relating to relational and cognitive learning. Hence, the theories presented can be used to model group interaction and group dynamics resulting from conformity and power relations.

Theories for modeling learning and cognitive biases used to model social influences, as well as their implementation, are also described in Papers III and IV.

2.4.4 Efforts to simulate emergent group phenomena in this thesis

In the first part of this section I clarified the scales on which concepts and processes can be ranked. This classification allows the separation of the micro level of implemented concepts from the macro level of emergent outcomes, as illustrated in Figure 8. Subsequently, I discussed the concepts and processes used to implement the micro level of CollAct. These are placed at the low level of the scales social (because individual actors are modeled) and depth of learning (because without the interpretation of new information from their environment actors are mere reactive). For the third scale, form, the implementation is at a medium level, because mental models are implemented as relatively enduring. During a simulation run, emerging outcomes on higher levels arise and which feed back into the running simulation. Interactions at the group level and perceived consensus are at a higher social level. Learning in mental models may occur, connoting double loop learning, and changed mental models influence the further run. Last, the group model is a product, ranking higher on the 'form' scale. The group model also influences actors and therefore the simulation.
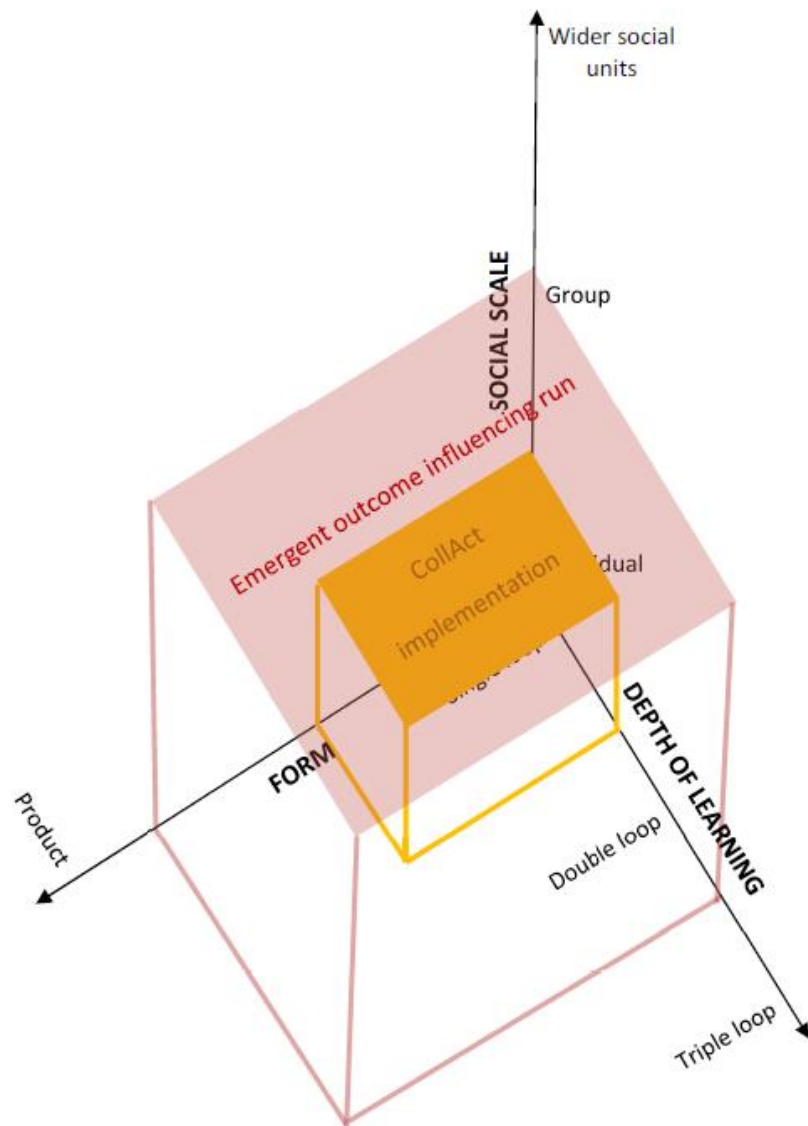
Fig. 8: Processes on certain levels produce emergent outcomes on other levels, which produce feedback to the simulation run.

3   METHODOLOGIES

This chapter presents the methodologies I used in this thesis. To acquire an overview of relevant issues and to answer RQ1 the first step was an extensive literature review, presented in Chapter 2. Various fields of science address aspects of social learning facilitated through participatory methods, e.g., natural resource management and resilience research, action research, organizational research, team learning, small group research, and social psychology. Therefore key publications could be identified in various communities.

Chapter 3 starts with a description of how the framework for analyzing social learning facilitated through participatory methods (Paper I) was created, and how methods were proposed to measure suggested indicators (Papers I and II). In the second part, the model building endeavor is described; from a literature review of similar models and the creation of a conceptual model to the implementation of a simulation model and the evaluation process.

3.1   CREATION OF A FRAMEWORK FOR ANALYZING SOCIAL LEARNING FACILITATED THROUGH PARTICIPATORY METHODS

Social learning is a vigorously debated concept that attracts researchers from diverse backgrounds (Swartling et al., 2011). Thus, no clear scope or common framework exists that could have been used to build upon. As starting point for a framework capturing the main elements and processes, I use the Management and Transition Framework (MTF), which was developed by Pahl-Wostl and colleagues to allow for the more precise analyses of water management processes (Pahl-Wostl et al., 2010). The MTF is a conceptual and methodological framework which addresses the dynamics and adaptive capacity of resource governance as multi-level learning processes by integrating concepts from various fields of research (Pahl-Wostl, 2009). It offers a standardized language to facilitate comparative case study analyses, while being flexible in addressing a range of research questions. Thereby special emphasis is placed on social learning and institutional change. Subject to analyses are the social system, actors, the water system, and the interactions between social and ecological systems.

To be able to analyse social learning in detail, I adapt the MTF to a specific setting, namely facilitated group processes, in Paper I (Chapter 4). Furthermore I broaden the already included mental model concept. The adapted framework is built for two possible applications: comparative case study analyses, and the building of a simulation model. To serve the latter purpose it had to incorporate clear concepts and definitions. As part of Paper I, I developed indicators to measure whether or not social learning occurred. The indicators are built upon the definition in Reed et al. (2010), and include an additional condition: the convergent direction of learning, referring to an increased overlap in mental models. An explanation of the choice of the definition in Reed et al. (2010) is contained in Section 2.1.2; the choice is based on a literature review of social learning in natural resource management.

Methods to measure the proposed indicators are based upon the results of the literature review presented in Chapter 2. For an evaluation of the extent to which individual mental models are merged into a group model, I could not find appropriate methods. Therefore, I searched for methods used for another purpose that could be adapted to this task. Massey et al. (1997) used methods for exploring the impact of individual characteristics on group support systems that are also appropriate for a comparison of individual mental models and a group model. To test these methods, data of three group model building exercises from the German-Austrian project PartizipA (Participative Modeling, Actor and Ecosystem Analysis in Regions with Intensive Agriculture) was available. PartizipA was carried out from 2003 to 2007 at the Institute for Environmental Systems Research (University of Osnabrück) and the IFF Social Ecology in Vienna, and involved two case studies in agricultural regions facing European policy-induced institutional change (Newig et al., 2008). The selected methods were applied to the data set from PartizipA in a Bachelor's thesis written by Martina Austermann (Austermann, 2012). The results are presented in Paper II (Chapter 5).

3.2 BUILDING AND EVALUATING COLLACT

In this thesis, an agent-based model is built to integrate knowledge from various strands of research, and to explore the dynamics that may occur due to group interaction during the application of participatory methods. In the following I describe how this was accomplished. I start with a short literature review of related models.

3.2.1 Literature review on related models

Various approaches exist which simulate learning. Brenner (2006) provides an overview of learning models used in economics. He finds that there is no single universal learning model, due to the context dependent and individually differing learning that can take place. He proposes a classification of learning models, of which my approach may be best described as conscious learning or belief learning, based on psychology. The stochastic belief learning Brenner proposes served as an inspiration for CollAct, as did his listing of knowledge about cognitive learning (see Brenner, 2006). However, Brenner focuses on economic learning. Relational learning is not considered.

I chose mental models as the core concept of CollAct (see Chapter 2 for reasons for this decision). Mental models have been used in agent-based models before by Edmonds (Edmonds, 1999), who models agents with a population of mental models (each agent having several mental models) which evolve. I wanted to include relational and cognitive knowledge and learning in CollAct to be able to simulate processes identified as important for group interaction (see Chapter 2). As a result, I use the explicit modeling of mental models of participants. Participants

in CollAct have only one mental model. Furthermore, the mental models of participants are split up into a substantive and a relational part, and both parts can change through learning.

While there is a growing body of literature on opinion dynamics models (e.g., Deffuant et al., 2002; Hegselmann & Krause, 2005; Jager, 1990; Lorenz, 2007; Meadows & Cliff, 2012), agent-based models considering more complex communication are still rare. A recent exception in the context of opinion modeling is presented by Dykstra et al. (2013), who develop a model of group dynamics and opinion dynamics, in which agents communicate and gamble about reputation points.

In CollAct, agents actively engage in a discussion over their opinions, and jointly construct a consensus. Arguments for using a complex cognitive model for the task of this thesis can be found in the literature: Conte and Paolucci (Conte & Paolucci, 2001) develop a framework for intelligent social learning, pointing out the need to include cognitive reasoning (e.g., the possibility of knowledge comparison and knowledge about other agents) to go beyond the simulation of social contagion. Furthermore, Barreteau and Le Page (2011) suggest the possibility of using social simulation to explore dynamics occurring in participatory research, including the micro level processes of knowledge construction within collaborative settings. In the tradition of modeling norms, Troitzsch (2012) reflects on simulating communication and interpretation during interaction, pointing at the need to model the interpretation of messages, memory, and deliberation processes. His ideas of simulating messages as tuples of information and using event-action trees to simulate decisions served as an inspiration for CollAct.

At the other end of resolution, there are models focusing on more detailed processes, or on specific elements of discussions. Two models of participation during face-to-face unstructured discussion are described by Stasser and Vaughan (1996). These models are able to reproduce certain patterns of participation in discussions. To keep CollAct clearly arranged and thus allow for an analysis of effects I left out such more detailed speech interaction influences, but kept an interface that allows for easily extending CollAct with probabilities for a participation in the discussion depending on more factors. Furthermore, I decided not to use the concepts provided by Agent Communication Languages (ACL) (see for example, Labrou et al., 1999). CollAct aims to simulation a discussion at a highly abstract level, thus neither syntax nor semantics are needed for the messages. Additionally, CollAct is not built to operate with other models, but rather as a stand-alone exploratory thinking tool. Thus, a connecting conceptual framework for communication is not necessary, and would only cause further complexity.

3.2.2 Building the conceptual model

The data from three group model building exercises conducted during PartizipA (see previous section) served as inspiration for the conceptual model underlying CollAct. As the main research question for the model, I chose the building of a shared understanding (as a key feature of social learning) while trying to reach a consensus in a group discussion. I approached this

question from the individual and group level. To accomplish this, I identified elements and processes at the micro level to implement CollAct and outcomes at the macro (group) level to validate whether or not CollAct produces realistic results based on the literature review presented in Chapter 2.

The structure of CollAct, including elements and processes linking these elements, is based upon the framework developed in Paper I of this thesis. This framework is adjusted to the modeling purpose in Papers III and IV. I focus on processes important in group level interaction which may result in social learning. Therefore I focus on cognitive and relational aspects, and as influences conformity and relational aspects including power and sympathy. To model influences and processes, I build upon the literature review presented in Section 2.4.3. Furthermore, I operationalize the indicators developed in Papers I and II to validate the model and evaluate the model output.

3.2.3 Implementation, simulation, validation, and evaluation

CollAct is implemented in Repast Simphony (North et al., 2013) (version 2.1) using Java. Repast Simphony is an open-source platform for agent-based modeling providing helpful basic functions. During the implementation phase of CollAct, new model functionalities were added in steps: Starting with a basic discussion model, adding mental models in the next step, and then adding roles, integrating cognitive biases, and learning in the last step. This process allowed the testing of the smaller model versions, and comparison of the model results to the expected results. Throughout this process I discussed the different model versions with experts who have experience with participatory processes and group model building in particular. Nevertheless, CollAct contains a number of parameters that could not be set on the basis of empirical evidence or theory. Unfortunately, empirical evidence is not sufficient to estimate parameters for learning models (Brenner, 2006). However, CollAct is an explorative model, aimed at illustrating the basic dynamics and link them to stylized facts. For such a study, using parameters that approximate the real values and conducting parameter sweeps to estimate the influence of parameter changes is sufficient and commonly used (Brenner, 2006).

Because of the explorative character of CollAct an explicit validation other than expert feedback is difficult. For validation I looked for group phenomena which could serve as stylized facts to test whether or not it is possible to reproduce realistic results with CollAct. The social psychological limits of participation listed by Cooke (2001) (see Section 2.2.4) provide a good starting point. While these are rather extreme phenomena they describe how social influence (implemented through the relational model and cognitive biases within CollAct) may lead to unwanted dynamics and decisions. Further research on group dynamics is found in social psychology (e.g., Baron & Kerr, 2003). Because CollAct does not include emotions and influences other than the ones described above, not all aspects of group phenomena can be displayed (e.g.,

in-group/out-group perceptions and the establishment and reproduction of norms and interaction rules cannot be represented with CollAct). Nevertheless, conformity and relational influences are grasped. While interpreting the results, some validation can be done 'on the way': every reasonable result which is confirmed through empirical finding is a further little step for validation. To validate and evaluate CollAct, a couple of parameter sweeps were conducted, varying the strength of assumptions (cognitive biases and learning) and the value of parameters. Results were summarized and handled using R (R Development Core Team, 2013), a free software program which provides graphics and statistical computing. For various parameters and indicators, I calculated the Spearman correlation coefficient to display the main relationships. Next, the identified correlations were compared to empirical data, to validate CollAct as far as possible at this stage. Furthermore, the main correlations were mapped back to reality and interpreted in a qualitative way. The results are described in Papers III and IV.

The source code of CollAct is placed in the appendix of this thesis. Additionally, a running version of CollAct can be found in the CoMSES Net Computational Model Library (https://www.openabm.org/model/4255/version/1/view)[12].

The next four chapters contain the articles which are part of this cumulative thesis. Due to the need to describe CollAct and discuss the basic results Papers III and IV partly overlap. All articles are displayed in original wording and layout as far as possible.

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[12] This link leads to the website where the model is placed at. Currently the model is unpublished, but visible with the direct link. It will be published after Papers III and IV are published.

4 PAPER I: AN ANALYTICAL FRAMEWORK OF SOCIAL LEARNING FACILITATED BY PARTICIPATORY METHODS

An Analytical Framework of Social Learning Facilitated by Participatory Methods

Geeske Scholz • Art Dewulf • Claudia Pahl-Wostl

Abstract Social learning among different stakeholders is often a goal in problem solving contexts such as environmental management. Participatory methods (e.g., group model-building and role playing games) are frequently assumed to stimulate social learning. Yet understanding if and why this assumption is justified is quite limited. Difficulties arise from the complexity and context-dependence of processes influencing social learning. Furthermore, continuing discussion of the exact meaning and theoretical basis of social learning result in a limited capacity to assess and evaluate whether social learning has occurred. In this paper we introduce an analytical framework to develop an in depth understanding of essential processes underlying social learning facilitated by participatory methods. Concepts from different fields of science are discussed and integrated, including resource management, small group research and learning research. The individual and group perspectives are brought together via mental models and emergent roles. We added the direction of learning, being either convergent or divergent, to be able to explore if and when personal views on a problem converge into a shared understanding of a problem. The analysis of convergence and divergence of learning is facilitated through the use of the mental model concept. Methods for measurement of proposed indicators for social learning are also discussed. The framework developed provides a conceptual basis for the analysis of social learning facilitated by participatory methods and an operationalization for application in empirical research.

5 PAPER II: EVALUATING GROUP MODEL BUILDING EXERCISES: A METHOD FOR COMPARING EXTERNALIZED MENTAL MODELS AND GROUP MODELS

Published as:

Evaluating group model building exercises: a method for comparing externalized mental models and group models

Geeske Scholz, Martina Austermann, Kai Kaldrack and Claudia Pahl-Wostl

Abstract
We introduce a systematic method to compare externalized mental models with a group model resulting from a group model building (GMB) process. To this end, we categorize the various concepts included in the models, and propose Venn diagrams and matrices to demonstrate the composition of the group model and identify the overlapping categories. We then suggest a set of metrics to analyze the matrices. We apply our method to a dataset of three GMB processes, finding the suggested method to be helpful for evaluating the extent to which all participants were able to include their perspectives, and whether new ideas emerged from the process, thus constituting innovation. We conclude that our method may be a valuable contribution to the evaluation of GMB processes. Furthermore, we demonstrate that the categorization of the concepts is a delicate process and has a significant influence on the results.

Introduction
In general, the participants in a group model building (GMB) process jointly develop a model of a specific problem at hand (Andersen and Richardson, 1997; Vennix, 1996). This allows for the capturing and integrating of diverse knowledge and perspectives. An additional goal is the development of a shared understanding of a problem, thereby facilitating joint action to address the problem (Vennix, 1996). However, what has been communicated by whom has received comparatively little attention. It remains difficult to evaluate the influence that the individual participants of a GMB exercise have had in the process, and to analyze the impact of GMB in developing a shared understanding among participants.

In this article, we propose a method to compare various aspects of individual mental models (elicited prior to a GMB exercise) with a group model (the result of a GMB exercise) in order to analyze the influence participants had on the outcome: the group model. In addition, our method is capable of evaluating: (i) whether all participants were able to include their points of view; (ii) how the facilitator performed in balancing the inputs of participants; and (iii) whether new concepts resulted from the process, thus constituting innovation. Approaches used to compare the viewpoints of individuals, a Institute of Environmental Systems Research, Osnabrück University such as the Q methodology (William, 1953; Van Exel and De Graaf, 2005), often rely on prior preparation of the setting (e.g. a sample set of concepts that should be sorted). In contrast, our methodology is applicable to diverse GMB exercises. The only prerequisite needed for our method is the collection of individual models in addition to the group model. Some scholars elicit individual models prior to the GMB exercise to investigate mental models of individuals (Halbe et al., 2015; Kim, 2009). In these cases, data for our method are gained without extra costs.

In the next section we begin by defining what we mean by mental model, individual model and group model, and summarize the various efforts in the literature to capture them. We also highlight the shortcomings of these methods. Next, we propose a matrix-based method to capture the concepts used in mental models and the group model resulting from a GMB exercise. This includes a categorization of and displaying the data in a matrix and a Venn diagram. Matrices are then reordered using the rank order clustering algorithm (King, 1980). We define variables and metrics to analyze the structure of the resulting matrix. We then apply our method to a dataset of three GMB processes, emphasizing the insights resulting from our method. In addition, we illustrate that the categorization of the concepts is a delicate process because the level of abstraction influences the results of the subsequent comparison. We conclude by discussing the limitations of our method and identifying potential areas for future research.

Individual models and group models

According to Doyle and Ford (1999), "[a] mental model of a dynamic system is a relatively enduring and accessible, but limited, internal conceptual representation of an external system whose structure is analogous to the perceived structure of the system" (p. 414). Different approaches have been used to elicit mental models in the various scientific fields (Massey et al., 1997; Jones et al., 2011). Nevertheless, finding adequate techniques for the elicitation of mental models remains a central challenge (Jones et al., 2011) because mental models are not directly observable and can change during the elicitation process (Doyle and Ford, 1998). Mental models cannot be captured one to one in external models because results are influenced by the internal mental model, the elicitation method employed and the mental model of the facilitator/modeler (Kim, 2009). Various qualitative mapping techniques have been employed to capture mental models, including causal loop diagrams, stock/flow diagrams, cognitive maps and concept maps. Henceforth, we refer to all these diagrams as individual models or group models. A group model is su posed to capture the point of view of the group, which is linked to the idea of a shared understanding. Nonetheless, this has to be treated with care. As with individual models, a group model should not be confused with the phenomenon of a "collective mental model" because elicitation and modeling assumptions will influence the result (Kim, 2009).

A comparison of concepts included in participants' concept maps to assess mental model changes has been carried out previously (Fokkinga et al., 2009). Most studies compare changes in mental models within subjects, while only a few compare mental models between subjects (Schaffernicht and Groesser, 2011). In this article, we focus on a comparison between individual models and a group model resulting from a GMB exercise.

A method to compare individual models and a group model

In this section we introduce our method to compare individual models and a group model based on a categorization of the concepts included in the models. We start with the process of coding concepts into categories to enable a comparison of concepts with similar meanings.

Categorization

The categorization process represents an inductive content analysis, which is a flexible method without simple guidelines and therefore delicate to conduct (Elo and Kyngäs, 2008). Concepts that refer to a similar phenomenon are grouped into one category. Categories resemble a title or caption for concepts included in the models and can be more or less specific (Kuckartz, 2010). Looking at the concepts individually, one has to decide whether the concept fits into an already existing category or produces the need for a new category. Categories can be specified with terms or short sentences. They should be set at a fixed level of abstraction, which has to be selected at the beginning of the data analysis (Mayring, 2010). Since the level of abstraction influences the results of the subsequent comparison, it should be chosen in a careful manner. Insufficient definitions of categories and non-mutually exclusive categories render a content analysis useless (Stemler, 2001). Additionally, background knowledge of the topic is needed to interpret concepts and create respective categories. A second categorization done by a different researcher may add to the validity of the results. For some data collection methods categorization becomes superfluous, e.g. if participants chose predefined concepts from a given list, these concepts are taken as categories because they are already comparable.

The method proposed in this paper is applicable to different types of categorizations as long as the categorization chosen is mutually exclusive. Furthermore, all concepts found in individual models and the group models should fit into a category.

Venn diagrams

Venn diagrams constitute a possibility of visually displaying and comparing data from individual models and the group model. These diagrams were introduced by Venn (1880) and reveal all possible logical relations of a finite number of sets. Massey et al. (1997) used Venn diagrams to capture the degree of homogeneity of individuals assigned to a group according to their mental models. We use Venn diagrams to graphically capture and display homogeneity and heterogeneity of the participants' individual models and the joint group model. In our Venn diagrams, all individual models and the group model are represented as sets, while the categories included in each model represent the respective elements. The Venn diagrams show how the group model is composed of categories from individual models and of further categories included during the GMB process (see an example of a Venn diagram in Figure 2). We recommend this visualization for groups with up to five participants to maintain clarity.

Matrices

Individual models and the group model can also be depicted in a binary matrix. To this end, the rows of the matrix represent the individual models of participants, while the columns represent categories. The group model is treated like an individual model of an additional participant. The matrix has binary items, which means that a 1 at the position (i, j) signifies that category j occurs in the individual model of participant i, while a 0 signifies that participant i did not use category j. Such a matrix provides the possibility of comparing individual models and the group model, as well as analyzing to what degree individual models and the group model overlap in terms of categories.

ROC algorithm

Reordering the matrix allows simplifying the analysis. A reordered matrix containing well-arranged data may at a glance give a first impression of the distribution of categories, which can then be followed up by a more sophisticated analysis. The rank order clustering (ROC) algorithm we use was originally developed by King (1980). Massey et al. (1997) used the ROC algorithm to allocate participants in groups depending on mental model similarities, which allows for generating homogeneous or heterogeneous groups with respect to mental models. The algorithm is used to gain a block diagonal layout of the matrix within a finite number of steps. A block diagonal layout refers to a matrix where diagonal elements of the matrix are ordered in blocks (square matrices of a smaller size than the overall matrix), which can be identified as clusters. Through these clusters, participants with similar individual models can be identified. This knowledge can be used to allocate participants in groups and to study impacts on group processes (Massey et al., 1997). We use the ROC algorithm to get a general idea about which categories and participants can be grouped together. It is also possible to observe whether a particular participant shares the view of the group model (being in the same cluster) or not (being in distinct clusters). The ROC algorithm may be applied to the binary matrix introduced earlier. Rows and columns are treated as binary numbers. Initially, rows are reordered, descending from top to bottom. Afterwards, columns are reordered from left to right. This procedure is repeated until no more changes are needed. A pseudo-code description of the algorithm is presented in Figure 1. We will illustrate a reordered matrix later in the paper.

A is matrix of dimensions mxn, where m is the number of models and n is the number of categories

```
S<-ROC(A)
S<-A initialize sorted matrix S to A
repeat
        B<-S set B to the current sorted matrix S
        for each model i in m
                R[i]<-0 initialize row counter
                for each category j in n
                        R[i]=R[i]+B[i,j]*2^(n-j) calculate row binary product
        end
        T<-B[Sort_d(R),ALL] set T to row-sorted B
        for each category j in n
                C[j]<-0 initialize column counter
                for each model i in m
                        C[j]=C[j]+T[i,j]*2^(m-i) calculate column binary product
        end
        S<-T[ALL,Sort_d(C)] set S to column-sorted T
until B=S stop when no changes in the sorted matrix S
```

Where
Sort_d(X) function returns indices of vector X sorted, in descending order, by the content of X and ALL refers to the unaltered order of indices of a matrix

Fig. 1: Pseudo-code for the ROC algorithm (based on King, 1980)

While the application of the ROC algorithm does not necessarily lead to a matrix with a block diagonal layout, reordering the initial matrix simplifies the analysis and helps in gaining a first impression of how individual models and the group model relate to each other.

Analysis of matrices with guiding questions

A spreadsheet program is used to analyze the matrix in more detail. Keeping in mind the objective of our analysis (i.e. to compare individual models and group model), we compare rows and columns of the matrix. We define metrics in Table 1 that help in interpreting the results. A short overview of interpretations of the presented metrics is provided after Table 1. We attempt to simplify this description using the following variables:

- A = Number of categories of the respective group (appearing in individual models and the group model)
- B_i = Number of categories found in the individual model of participant i
- C_i = Number of categories found in the individual model of participant i and the group model
- D = Number of categories appearing in the group model
- $E_0, E_1 \ldots E_n$ = Number of categories appearing in the group model and in the individual model of none, one, or n participants (n being the number of participants as upper bound)
- $F_{i0}, F_{i1} \ldots F_{in-1}$ = Number of categories appearing in the individual model of participant i, the group model, as well as in the individual model of none, one, or $n-1$ other participants (n being the number of participants)

Table 1 may be interpreted as follows:
- **Comprehensiveness** means that many different ideas (categories) can be found in a model. A small share of categories may indicate an imprecise or biased point of view. The individual model or group model could even include many concepts, referring to only a few categories. By contrast, high comprehensiveness resulting from many categories may indicate a broad view of the problem. In general, it is important to keep in mind that the appearance and minutiae of individual models also depend on elicitation methods and skills of the interviewer (Eden and Ackermann, 1992). Hence comparing individual models from different projects in absolute terms may be questionable, while comparing individual models from one project where similar methods were used and the same interviewers were active is possible.

- **Commonness** helps us to learn how important a category is for the group as a whole. The more participants choose a specific category, the higher is the apparent importance of the category regarding the issue at hand.

Table 1: Metrics to interpret the matrix of categories (n being the number of participants)

Metric	Computation	Description
Comprehensiveness	B_i/A or D/A	Relative share of categories chosen by a participant respectively by the group.
Commonness	Number of individual models that include a certain category/n	Share of participants that included a category in their individual models.
Shared portion	E_x/D	Fraction of categories of the group model which also appear in none (one/more) individual models.
Shared categories	C_i/B_i,	Share of categories of the individual model of a certain participant that are also parts of the group model.
Indication of influence	C_i/D	Share of the categories of the group model which are also parts of the individual model of participant i.
Indication of individual influence	F_{ix}/D	Share of categories of the group model that are also found the individual model of a certain participant and in none (one/more) individual models of other participants.

- The **shared portion** of categories of the group model which also appear in none (one/more) of the individual models tells us whether the group chose more unique categories among those proposed or more categories which were included in most individual models before the session. For example, categories that appear only in the group model and in no individual model relate to ideas generated from the GMB exercise. Thus the shared portion helps in estimating the amount of learning that took place.

- **Shared categories**, the **indication of influence** and the **indication of individual influence** help in interpreting the extent to which a participant was involved in the process and managed to implement his or her own ideas. If many categories in the individual model of participant i also appear in the group model (high value for shared categories), this may indicate that i became involved in the process and actively participated in the group. Additionally, if a large share of the group model is composed of categories only i had in their individual model (high individual influence as indicated by a high value for F_{i0}/D), this may indicate that i was able to promote their view and impose this on other participants. If, on the other hand, there are only a few shared categories of the group model and the individual model of participant i (low value for C_i/B_i), this would indicate that participant I did not have a lot of influence and was not dominant in the process. Either participant i had to make many compromises or they may have changed their own view during the process.

Application case: PartizipA

In the following section, we apply the introduced methods to data from a case study to demonstrate their application and usefulness in practice. We use data from the German–Austrian project PartizipA (Participative Modeling, Actor and Ecosystem Analysis in Regions with Intensive Agriculture). Carried out from 2003 to 2007 at the University of Osnabrück and the IFF Social Ecology in Vienna, PartizipA involved two case studies in agricultural regions facing European Union-induced institutional change (Newig et al., 2008). Thus different participatory methods have been employed. The data we use stems from the German case study that focused on the implementation of the European Water Framework Directive (WFD) in the region north of Osnabrück. In this region, intensive poultry and pig farming has led to high nitrate levels in groundwater, compelling a demand for measures to fulfill the requirements of the Directive (Newig and Kaldrack, 2007). During PartizipA, possible measures were discussed for a reduction in the nitrate intake (Berkhoff et al., 2006). We have treated the data independently of the PartizipA project, taking an outsider perspective and focusing on the GMB process embedded in the actors' platform.

Process

Fourteen stakeholders from different sectors (water management, agriculture, environmental protection, administration) participated in the actors' platform (Berkhoff et al., 2006). The process in the actors' platform followed four main phases: exchange of information and creation of a common ground, modeling, use of simulation models to facilitate social learning and the preparation of a regional guideline with recommendations. The GMB exercise took place during the second phase (modeling), hence our focus on this aspect of the process. The modeling phase started with the elicitation of individual mental models in face-to-face interviews of 90 minutes' duration, focusing on regional challenges arising during the implementation of the WFD and their interdependencies. After the interviews, the resulting individual cognitive maps were post-processed digitally by the researchers, verified by the respective interviewee and printed as posters. Within three small groups, each actor presented his/her poster in a 10-minute presentation. After clarifying issues related to comprehension of meanings, the participants discussed similarities and differences in their perspectives and merged their views in one shared cognitive map in each of the groups. For this purpose, the project team had analyzed the cognitive maps beforehand with regard to similarities, and introduced a basic causal diagram with elements and interrelations that could be found in all individual cognitive maps. After discussing this basic diagram, the participants identified concepts missing in this representation and added them to the shared cognitive map of each group. Furthermore, they discussed causal relations and interdependencies. During the small group meetings, one participant of each group was absent.

Analysis

We analyze the three groups independently. To present data through matrices and Venn diagrams, we include absent participants. In the subsequent analysis, we distinguish between present and absent participants. This is because the absent participants did not take part in the discussion, and thus it does not seem reasonable to measure how much they were involved in

it. However, their individual models may still have had some influence on the respective group model because they were introduced to the group members by the facilitator, and are therefore included in matrices and Venn diagrams.

Categorization

The first step of our analysis involves the categorization of concepts. This is done separately for each group. We subsumed concepts under categories as follows:

1. We combined concepts which followed the same idea. An example is "biogas plants" and "power production" were combined in the category "biogas".
2. Concepts compatible with each other with regard to content were merged into one category. An example is the category "financing", which includes concepts like "public funds" and "EU funding".
3. Concepts with a similar meaning in the specific context were included in one category. The category "nitrogen intake" includes concepts like "leaching of manure" or "nutrient input".
4. Different concepts were subsumed in one generic term, e.g. in the category "actors".

We arrived at 44 categories for the first group and 37 categories for the other two groups. Considering that results may vary depending on the level of abstraction (see method section), we conducted two categorizations with different levels of abstraction. For the second categorization, we chose a lower level of abstraction, resulting in more categories (76 for Group 1, 55 for Group 2 and 54 for Group 3). In this paper, we concentrate on the first categorization. We further provide a comparison of the results of both categorizations to show the differences.

Venn diagrams

Venn diagrams illustrate the distribution of the categories. Two Venn diagrams of Group 1 are displayed in Figure 2, whereby Figure 2(a) excludes the absent participant. In Figure 2(a), one can see how categories of the three attendant participants and the group model overlap. Two intersection sets are remarkable: the intersection set of all individual models (including four categories) and the set of categories only appearing in the group model. The latter seem to stem from the interaction process. Here we can see why it is important to consider the individual model of the absent participant, which includes category 14 (underlined). Hence category 14 does not stem from the interaction process. Figure 2(b) includes the absent participant's individual model. Here, we focus on the composition of the group model. The spotted intersection sets of Figure 2(b) contain categories appearing in the group model and in only one individual model, which indicates the individual's influence. The dashed intersection set is the overlap of all individual models and the group model.
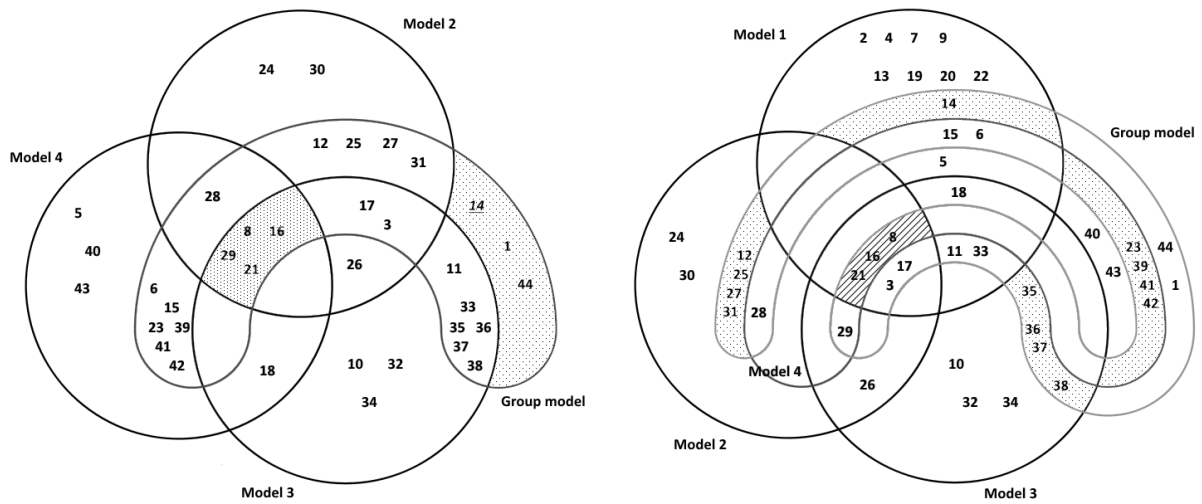
Fig. 2: Venn diagrams of Group 1 displaying the intersections of categories between participants and the group model. Fig. 2a does not include the absent participant (model 1)

Matrices and ROC algorithm

While Venn diagrams become very ineffective for groups with more than five participants, matrices can be used to capture data from larger groups. We transferred the categorized data to matrices and applied the ROC algorithm as described in the method section. Results for Group 1 are presented in Table 2. In the reordered matrix, it is visible which categories appear together and which categories of the group model stem from certain participants. Subsequently, we used a spreadsheet program to calculate the comprehensiveness, commonness, shared portion and the metrics that help to interpret the extent to which a participant became involved in the process and managed to implement their ideas.

	8	16	21	17	3	11	33	6	15	14	29	35	36	37	38	28	12	25	27	31	23	39	41	42	1	44	18	5	2	4	7	9	13	19	20	22	26	10	32	34	24	30	40	43
G	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1																	
1*	1	1	1	1	1	1	1	1	1	1																	1	1	1	1	1	1	1	1	1	1	1							
3	1	1	1	1	1	1	1				1	1	1	1	1												1										1	1	1	1				
2	1	1	1	1	1						1						1	1	1	1	1																1				1	1		
4	1	1	1			1	1				1					1					1	1	1	1			1	1															1	1

Results of the analysis of matrices

To illustrate the results of the spreadsheet calculations, we provide the results for Group 1 in Tables 3–6. We discuss the findings for Group 1 in detail, followed by a more concise comparative description of the results for Groups 2 and 3.

Table 3: Overall results of Group 1 (*absent participant, **without the absent participant, ****deviation from the mean)

	Overall categories (A)	Categories on model (B)	Overlap ind. models and group model (C)	Comprehensiveness (B/A)	Shared categories (C/B)	Indication of influence (C/D)
GM	44	26		59.1%		
1*	44	20	10	45.5%	50%	38.5%
2	44	14	11	31.8% -3%****	78.6% +4.4%	42.3% -1.3%
3	44	17	12	38.6% +3.8%	70.6% -3.6%	46.2% +2.6%
4	44	15	11	34.1% -0.7%	73.3% -0.9%	42.3% -1.3%
Ø*				34.8%	74.2%	43.6%

Table 4: Shared portions (E0, E1 ... En = Number of categories appearing in the group model and in the individual model of none, one, or n participants)

	E_0	E_1	E_2	E_3	E_4
	2	13	5	3	3
Shared portion (E_x/D)	7.7%	50%	19.2%	11.5%	11.5%

Table 5: Metrics for participants (*absent participant)

	Participant 1*	Participant 2	Participant 3	Participant 4
F_{i0}	1	4	4	4
Ind. influence (F_{i0}/D)	3.8%	15.4%	15.4%	15.4%

Table 6: Overlap between individual models 1–4 and the group model (GM)

	1	2	3	4	GM
1	100%	57.7%	69.2%	57.7%	38.5%
2		100%	57.7%	53.8%	42.3%
3			100%	42.3%	46.2%
4				100%	42.3%
GM					100%

Group 1

As can be seen in Table 3, the group model (GM) is more comprehensive than each of the individual models. This means that Group 1 adopted a broad view of the problem compared to the individual perspectives of the participants. In doing so, they integrated a diversity of categories that were each only included in one individual model and therefore brought in by a single participant (50%; see Table 4, E1). On the other hand, three categories were chosen by all Table 2. Matrix of Group 1 after reordering with the ROC algorithm (*absent participant, G refers to the group model) participants and included in the group model (see E4 in Table 4). Three more categories were chosen by more than half of the participants and included in the group model (see E3) ("monitoring", "education & guidance" and "number of cattle"). These categories have a high commonness and appear to be particularly important for the participants. Two categories ("awareness & acceptance" and "economic situation of farmers") are found only in the group model (see E0); thus they seem to stem from the interaction process and may constitute learning during the GMB exercise. The share of categories from individual models that are included into the group model is high, on average (see Table 3 shared categories). It is lowest for participant 1, which seems evident because this was the absent participant. The indication of influence is balanced for all participants (from 38.5% to 46.2%). Likewise, the indication of individual influence does not differ for any participant (besides the absent participant), implying that no participant was either dominant or had negligible influence (see Table 5). Interestingly, one category of the group model can only be found in the individual model of the absent participant. Table 6 quantifies the similarity of perspectives of different participants that is visualized in Venn diagrams and matrices (Figure 2 and Table 2). For Group 1, participants 1 and 4 have the largest overlap (69.2%), while participants 3 and 4 have only 42.3% of categories in common.

Comparison of group results

While categorization has been done separately for each group, and thus a direct comparison is not possible, a comparison of variables and metrics can be done. In all groups, the group model is most comprehensive with respect to the number of categories, thus including more ideas and perspectives. In Group 3, this is not as significant as in the other groups (51.4% of all categories are included in the group model) due to the individual model of one participant being highly comprehensive. The average share of categories of participants with the group model is also lower in Group 3 (see Table 7, shared categories). For Groups 2 and 3, no category appears in all the individual models and in the group model (see En/D). Thus, in contrast to Group 1, the overlap of perspectives in Groups 2 and 3 was minor at the beginning. As for Group 1, approximately half of the categories of the group model of Group 2 appear in only one individual model (see E1/D); thus a diversity of categories was integrated from distinct perspectives. For Group 3 this value is slightly lower (42.1%).

While the individual influence of participants was balanced in Group 1 (as indicated by similar values of F_{i0} for participants 2–4 in Table 5), some differences can be observed in Groups 2 and 3. For Group 2, the indication of individual influence varies strongly between participants, with a range of 54.2%. Thus the involvement of participants and their influence on the results

are unequally distributed. The same applies for Group 3. Here, one participant has fewer categories shared with the group model (45.5% compared to a group average of 59.6%). Different explanations are possible: weak involvement, scarce facilitation in not enabling all participants to speak up, or a perspective distinct from the rest of the group. In contrast, another participant has a high value of shared categories (63.2%) and a high indication of individual influence, bringing in 26.3% of the categories of the group model alone.

With regard to content, four categories have a high commonness and thus seem particularly important in at least two of the three groups: "education & guidance", "funding", "Directive/guidelines" and "land use/agricultural use". In each group, two categories appear only in the group model and thus seem to stem from the interaction process. Categories that can be found only in the group model could be specifically interesting when it comes to the analysis of learning, particularly social learning (Fokkinga et al., 2009).

Comparison with second categorization
For the second categorization, some differences can be observed. Owing to the more detailed categories, the overlap of group models and individual models is minor (see Table 7, shared categories). Furthermore, fewer categories can be found in the individual models of all participants and the group model (E_n/D), while more categories are shared by the group model and one individual model (E_1/D). The average commonness of categories is lower. In addition, in Group 3 slightly more categories of the group model appear in no individual model, and therefore are a result of learning in the GMB process (E_0/D). With regard to content, the main findings for categories emerging from the interaction process remain the same, while it is more difficult to identify categories with a high commonness also appearing in the group model. These results underline the sensitivity of the categorization chosen: the commonness of categories depends on the detail of the categorization.

Table 7: Comparison of first and second categorizations. Ex/D = Average share of categories of the group model appearing in the group model and in the individual model of x participants

	Comprehen-sive-ness (B/A)	Shared catego-ries (C/B)	Indication of influence (C/D)	Shared portion (Ex/D)		
				E_1/D	E_n/D	E_0/D
First categorizations						
ø **Group 1**	34.8%	74.2%	43.6%	50.0%	11.5%	7.7%
ø **Group 2**	29.7%	71.7%	33.7%	52.2%	0%	8.7%
ø **Group 3**	36.0%	59.6%	42.1%	42.1%	0%	10.5%
ø **First cat.**	33.5%	68.5%	39.8%	48.1%	3.8%	9.0%
Second categorizations						
ø **Group 1**	28.1%	61.0%	33.3%	71.8%	2.6%	7.7%
ø **Group 2**	25.9%	56.1%	29.6%	59.3%	0%	7.4%
ø **Group 3**	33.3%	40.1%	30.6%	54.2%	0%	16.7%
ø **Second cat.**	29.1%	52.4%	31.2%	61.8%	0.7%	10.6%

Discussion

In this paper, we introduced a method to compare individual models and a group model in various ways. For this endeavor, the categorization of concepts was a necessary and delicate process. Categorizations with different levels of detail lead to different results, as shown in this study. In some cases, a categorization may be superfluous when participants chose concepts from a list. In all other cases, categorization gives the scope to capture and compare similar thoughts.

To present our method, we focused on concepts and disregarded links in the models. Feedback loops, including delays and polarities, are an important feature of mental models of dynamic systems (Schaffernicht and Groesser, 2011). Nevertheless, we wanted to provide an easily applicable and clearly described method to compare individual models and a group model, and decided to start with a comparison of concepts included in the models because this is an efficient starting point for such a comparison. The method can be extended to include links between concepts. We plan to expand our method to the links included in models, and present an idea how this can be done in the future research section.

Considering mental models and collective mental models, the method introduced here may facilitate further research. Kim (2009) invited interdisciplinary efforts to develop methods to study what she called "group processor" (concepts similar to mental models at group level). Our approach is such an interdisciplinary effort, with the attempt to provide a simple method which can be used in a broad variety of cases. Still, conclusions about the group processor are delicate: when and how the integration of individual mental models into a result at the group level is carried out and how data are collected influence what is represented in the group model (Kim, 2009). This should be kept in mind and examined further with respect to the research interest.

Conclusions and future research

The method introduced in this paper helps in the analysis of the differences among individual models, the different perspectives comprising the group model, and the concepts that individual participants could add to the group model, thus estimating their influence. With regard to content, categories that are particularly important can be identified via their commonness. Furthermore, categories that appear only in the group model and in none of the individual models can be found, indicating that learning has occurred during the GMB process (Fokkinga et al., 2009).

Matrices and Venn diagrams present promising ways for visually comparing individual models and a group model. Venn diagrams are especially useful when it comes to smaller groups. For larger groups the readability is not convincing. Matrices can be used independent of group size. The ROC algorithm helps in the development of a clear matrix and facilitating comparison. Advanced analysis can be done using a spreadsheet program. An application of our method to larger groups is a next step for further highlighting what this method can add and which problems may exist in its application.

The categorization necessary to compare concepts included in models should be treated with care because the level of abstraction influences the results of the subsequent comparison. In general, the context of the project that is analyzed should be kept in mind. Additional material or inside knowledge is useful and necessary for a meaningful categorization and interpretation of results.

We disregarded relationships between concepts, though they are a core element of system dynamic models. However, matrices could be used to include and compare links between the concepts as well. One way of doing this could be to create a two-dimensional matrix in which rows and columns both represent the (same) categories. Next, links can be included by adding a 1 for every included link at the position in the matrix referring to this link. Thereby, a 1 at position (i, j) signifies that category j is linked to category i. In the next step, all identified links can be numbered and then treated like categories. Thus it is possible to conduct an analysis similar to that we proposed for concepts.

Our method could be linked to other approaches. The comparison of individual models prior to an intervention with group models and individual models after an intervention may support the analysis of social learning processes (Scholz et al., 2014). Furthermore, our method could be linked to an analysis of the long-term effects of GMB exercises as described by Scott et al. (2013). The combination of an analysis if all participants were able to include their points of view and of the learning that took place with an evaluation of long-term effects in participants could provide valuable insights into the effects of the design of GMB interventions. Another possibility is to use our method for the evaluation of the coding of purposive text data in qualitative causal maps (see Turner et al., 2013) in order to analyze the resulting model with reference to the contributions from a single stakeholder.

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6 PAPER III: AN AGENT-BASED MODEL OF CONSENSUS BUILDING

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An Agent-Based Model of Consensus Building

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Abstract—**Our model, CollAct is built around the question how people gain a shared understanding and reach consensus in an interactive group setting. This is an important question which is rather difficult to analyze within case studies. We model agents in a cognitive way, including substantive and relational knowledge in mental models, which may change through learning. The agents in CollAct discuss with each other and produce a group model (consensus). Factors identified to have an important influence on the results of a group discussion include group size, the level of controversy within the discussion, cognitive diversity, social behavior in form of cognitive biases (Asch and halo effect), and, depending on group size, the existence of a leading role at the beginning. Furthermore, the integration of topics into the consensus follows a saturation curve, thus the ending time of discussions should be carefully chosen to avoid a loss of information.**

I. Introduction

HOW do people develop a shared understanding and reach consensus in an interactive group setting? Interactive participatory settings are widely promoted in natural resource management and policy making [1],[2]. They are expected to promote social learning, and thus help to adapt to the growing complexity and uncertainty of today's world [1],[2],[3]. Therefore building a shared understanding of the issue at stake as well as reaching consensus is often considered a worthwhile goal. However, up to now only limited empirical research on the effectiveness of social learning and the development of a shared understanding is available, one reason being the difficulties in measuring and qualifying internal changes in individuals [4]. Limiting analysis to a specific event and thereby reducing context factors seems to be one reasonable strategy to enhance knowledge [5]. Furthermore, there is evidence which suggests that the process (e.g., group dynamics) may have more influence on the result than the choice for a specific participatory method applied to facilitate social learning [6]. These are arguments for the use of an explorative agent-based model, in which internal changes can be tracked and different processes and group dynamics can be simulated.

With **CollAct** (modeling **coll**aborative **act**ivities) we present such a model. CollAct allows to explore group dynamics in interactive discussion: When and how individual views on a problem converge into a shared understanding, how individual and group properties interrelate, how roles shift and emerge, and how a consensus can be achieved through discussion. However, economic factors and norms are not considered. Instead, CollAct builds upon speech processes, cognitive and social-psychological theories. Hence, our agents are modeled in a rather complex, cognitive fashion. To be in line with social-psychology, they consider both relational/social and cognitive aspects (own knowledge) to interpret incoming messages and to decide on their next action. As far as we are aware this has not been done so far.

We start with an overview of the conceptual framework our model is based on, also discussing empirical findings and concepts. In the next section we describe the conceptual model of CollAct, and discuss some important implementation details. This is followed by a presentation of simulation results and their interpretation. We end with a discussion of our approach, conclusions and an outlook on further research.

II. Conceptual Framework

CollAct is based upon an analytical framework of social learning facilitated by participatory methods [7]. This framework was developed to support an in depth understanding of processes underlying social learning. Our interpretation of this framework is presented in fig. 1. A core component in it, used to link individual and group perspectives, is the mental model concept. Mental models refer to "personal internal representations of the surrounding world" [7, p.6]. Every actor has a mental model. Mental models influence how information from the environment is interpreted, and therefore influence the relationship to the environment. They can change through learning. Thereby mental model is divided in two parts: the substantive model, which includes knowledge about the topic at stake, and the relational model, including knowledge about other actors (e. g. personal characteristics) and self-perception. Actors come together and interact an a

discussion. In this discussion every actor has a role (e.g., being active or passive), and change in the relational mental models of actors can manifest through the shift or emergence of roles. The substantive models influence the content of the discussion. Events in the discussion, on both relational and substantive levels, have a feedback on the individual mental models, which may again change through learning. Possible outcomes include relational outcome (e.g., better relationships), the building of a shared understanding, and, in our case, a group model as substantive outcome. In this group model we model the consensus which may be reached during the discussion. Consensus and shared understanding are not the same: Consensus refers to the result of the discussion (modeled as group model in CollAct), while shared understanding refers to the overlap of mental models of participants.
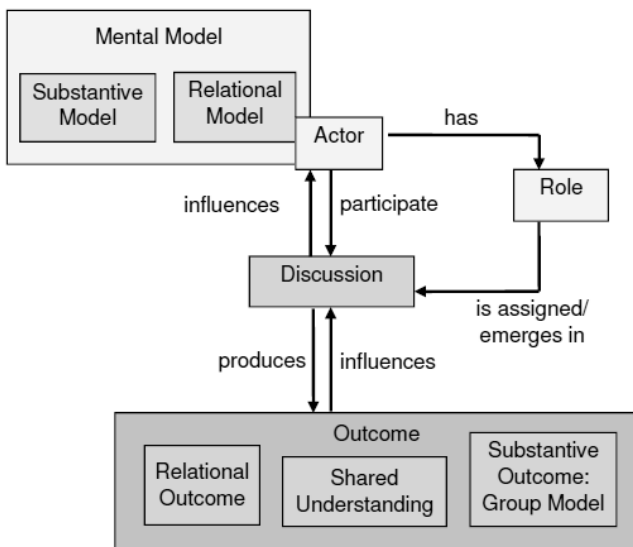
Fig 1. Conceptual framework underlying CollAct, derived from [7]

A. Theories used for CollAct

For learning and mental models a lot of research exists, e.g., [8],[9],[10]. To encounter new knowledge can lead to a change in concepts, respectively in the mental model [8]. People develop new concepts fast and on little evidence, and tend to keep these without strong evidence against them [9]. And, people are more likely to notice information that supports their assumptions (confirmation bias) [10].

We use two cognitive biases to model influences of the relational model: the Asch effect and the halo effect. The Asch effect [11] describes how people conform to obviously wrong judgments under perceived group pressure. The halo effect describes how a positive judgment of a person in one dimension (e.g., good looking, or sympathetic) creates a positive bias in the judgment of this person on any dimension (e.g., intelligent) [12]. These two cognitive biases are partic-

ularly useful because they help to include the relational influences included in the underlying framework in the decision part of agents. Furthermore, they help to model two main processes in group interaction: Conformation and the influence of roles.

An overview of included theoretical assumptions is provided in Table I.

III. MODEL DESCRIPTION

CollAct models an interactive group discussion. Thereby the discussion is modeled in a turn-taking manner, only one agent can speak at a time. Furthermore, all agents listen to every message. No facilitation or moderation of the discussion takes place. The agents discuss about a problem exchanging messages. If sufficient messages support a certain topic, it is included in the group model (consensus). The discussion goes on until either a sufficient long silence period occurs (20 steps per default), or time is over.

CollAct is implemented using Java in Repast Simphony [13]. Fig. 2 provides an overview of the speech process in CollAct. In the following, we give a short description of all classes, a more detailed description for the main decision part in participant, an overview of implemented concepts, and an overview of all parameters included.

A. Overview of classes

Model

Model is used to represent participants' substantive models and the group model. The group model represents the consensus of the group. The group model is held by the facilitator (which does not have an active part in the process), while the individual substantive models belong to participants. Model is arranged as a simple array with a predefined size (which can be set in the GUI), in which topics can be saved as Integers. Every field in the array refers to a specific topic. A one in this array fields means that the participant has this topic in her substantive model, respectively the topic is included in the group model (consensus), while a zero means the topic is not included. Model offers methods to add and remove topics, to check if a certain topic is included, to get the number of included topics, and to get a random topic included in the model.

Facilitator

The facilitator has no active part in CollAct (this may be changed in future implementations). The facilitator acts as an observer, who provides information about the current status of the consensus. This is done in the group model. The facilitator holds the group model, and adds new topics if a consent level is reached. This consent level is set to the number of participants. To keep track of the consent on topics, the facilitator sums up all messages in favor and against topics. Hence, in our implementation not all participants have to
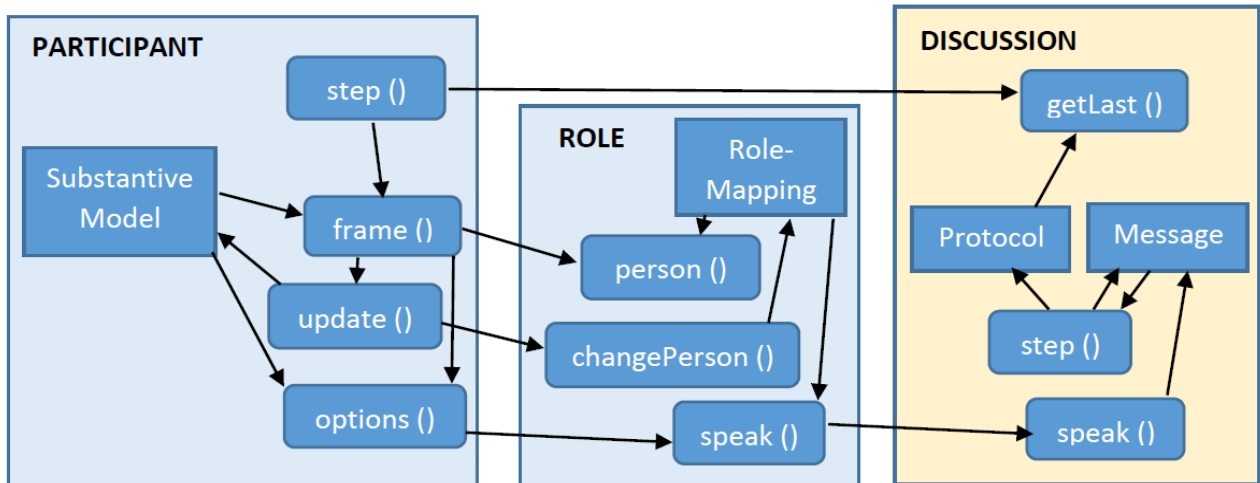
Fig 2. The speech process as modeled in CollAct. Details for participant, role, and discussion are described in the text (type of illustration based on [14])

agree on a topic to be included. If sufficient supporting messages are counted without dissenting votes, a topic is included in the group model. If the consent on a topic falls 2 below the consent level, topics are removed again out of the group model. Furthermore, the facilitator has a method to check whether a topic is included in the group model, and provides methods for the graphical display of model results and end routines for evaluation.

Participant

Participant is the main class of CollAct. Participants hold a model in which topics are saved, representing their substantive model. Furthermore they have a role, including self-perception and perception of others, representing their relational model. Participants interpret the last message concerning to the content (is the topic included in their own substantive model?) and the speaker. On these results they are able to learn (update their own substantive and relational model) and decide on further actions. During the update method participants can learn about roles depending on the similarity of opinions (if the topic proposed from participant A is also included in the substantive model of participant B), and about their substantive model. The probability of change in the substantive model depends on the perception of the speaker. Possible actions are implemented in the options() method, which is described more in detail later on.

Message

In message the inputs of participants to the conversation are modeled. Messages are tuples (speaker, topic, in) [based on 15] that provide methods for returning the value of each element (e.g., speaker). *Speaker* identifies the participant who sent the message, *topic* is a number and identifies the

topic the participant talks about, and *in* is a boolean which indicates if the participant wants to include or exclude this topic from the group model.

Role

A role belongs to a participant. Role provides the roleMapping in which the relational model of an agent is stored. RoleMapping is implemented as an array, in which the perception of other participants and self-perception are presented as real numbers between zero and one, one being the most positive and zero the most negative value. For simplicity, all kinds of different relational dimensions are summarized in this value, e.g., sympathy, competency, power, and attraction. Role provides a speak method that is called up by participant. Role then increases or decreases the probability for the message to be passed on, depending on the perceived position of the participant in the discussion. If a participant sees herself in a strong position (high role value compared to the rest of the group), the speech probability rises. If she sees herself in a weak position the probability decreases. Role then evaluates if the probability is high enough (by comparing it to a random number), and if so, calls up the speak method of discussion to register the message for the next step.

Discussion

Discussion represents a virtual room. All participants and the facilitator know their discussion, and can call up a method of discussion to "hear" the last spoken message (see fig.2). Furthermore, they can pass a message via their role. Role can register the wish to take part in the conversation by sending a message. Because CollAct models a turn-taking conversation, only one registered message per step is chosen
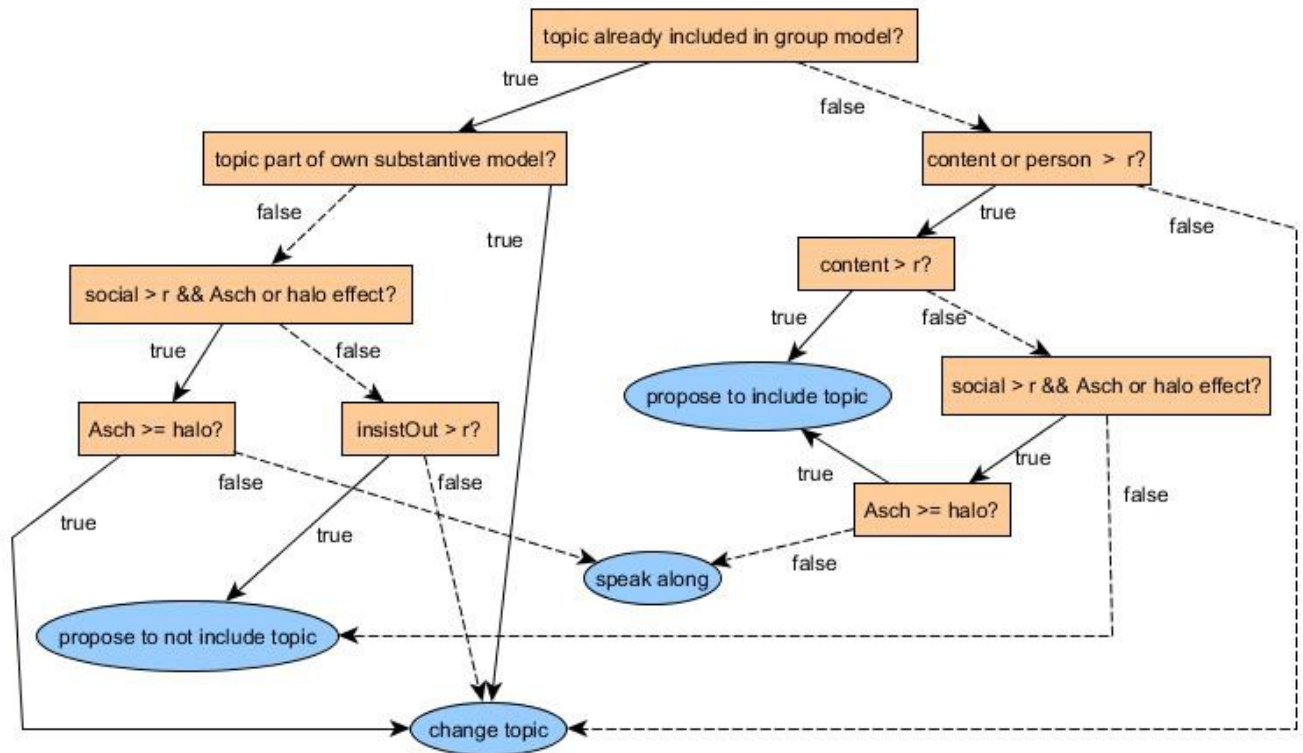
Fig 3. Decision tree in the options method of participant

by the discussion to be spoken out "aloud". Thereby it is decided upon randomly which message is chosen, using the implementation of Repast Simphony, which calls up the step methods of agents in a randomized way. Discussion saves chosen messages in a protocol, providing a shared memory. Furthermore this class provides end routines for the model evaluation.

Protocol

Protocol belongs to the discussion. It saves the last n (this depends on the parameter *forget*, which is set on 3 per default) messages with different topics in a consecutive order. Furthermore it saves n possible occurrences for each different topic. For example protocol may save three messages with topic A, one message with topic B, and two messages with topic E. When a new entrance is added, protocol restructures. Furthermore protocol provides a method which returns the most probable topic to speak about concerning the protocol. Thereby the probability for a topic to be chosen depends on its location in the protocol (higher for more recent topics) and its number of entrances. Another method provided by protocol returns how many different actors wanted to include a certain topic. The returned number depends on the number of possible entrances (forget).

SessionBuilder

SessionBuilder is a class required to run a Repast Simphony model. SessionBuilder manages the simulation by reading in parameters from the GUI, instantiating the other objects, and placing them in a context.

B. Detailed description of options

Here we describe one method more in detail: the decision method of participant, options(). Options() is implemented as decision tree. This may be best understood via pseudo code and a graph. Fig. 3 displays the decision tree implemented in options(). The ovals are possible actions: participants can propose to include the topic of the last message, propose to not include this topic, speak along (whatever the previous speaker said), or change the topic. The rectangles represent decisions on the way to a possible action. Thereby some of the values which are evaluated have been calculated by the interpret () method: content and person. Others, like *social* and *insistOut* are parameters which can be chosen in the GUI at the beginning. Finally, Asch and halo are calculated by asking how many other actors wanted to include a topic, respectively by looking at the role value of speaker. For example, one way trough the decision tree could be: the last message had a topic not included in the group model so far. Neither content nor person are higher than a random number, this means that the participant is just not interested in what

TABLE I.
CONCEPTS IMPLEMENTED IN COLLACT

Concept	Implemented in Participant in
Mental models influence perception, cognition and behavior	interpret(), options()
Asch effect	options()
Halo effect	options(), update()
People develop concepts quickly on little evidence and stick to them without strong evidence against them	update()
New knowledge can lead to a change in concepts	update()
Confirmation bias	options()

TABLE II.
PARAMETERS

Name	Description	Default
howMany	number of participants	6
ModelSize	capacity of substantive models	40
topicQuantity	to what extend are mental models of participants filled (randomly)	0.2
social	probability for halo and Asch effect	0.3
insistOut	probability to insist to exclude certain topics out of the group model again	0
learning	probability for learning	0.2
endAt	stopping time (end of session)	1000
forget	gives the amount of memory capacity for messages	3
freqProb	multiplier for frequency of a topic (in ProtocolItem, inner class of Protocol)	0.3
pm	probability to join in a topic also represented in myModel	0.3
p	probability to bring in a topic not represented in myModel from the protocol (to be not included in the group model)	0.05
openness	openness to topics not included in myModel	0.3
	evidence against concepts has to be ten times stronger to take them out as the evidence needed to include new concepts (in update)	
silenceStop	after this number of steps without speech CollAct is stopped	20
k	proportionality constant for logistic growth function for roleMapping update (learning)	0.5

has been said and who said it. Therefore the decision is to change the topic.

The change of a topic is implemented in another decision tree. In this, the protocol is asked for the most likely next topic, which is saved in the variable pt. The following pseudo code illustrates the further procedure.

pt = most likely topic from the protocol
p, pm = parameter (see Table II)

If (pt is included in own mental model and pm > random)
  propose pt
Else if (p > random) propose to exclude pt
Else propose new random topic of own mental model

C. Implemented concepts

Table I provides an overview of the theoretical considerations that were integrated in CollAct. These can be found in participant, where the most decisions take place. Table I also shows in which methods the concepts are used.

D. Parameters

All parameters used in CollAct are listed in Table II. The first seven parameters are placed in the GUI. We tried to keep the number of parameters as low as possible and base them on theory wherever possible. We concentrate on the parameters placed in the GUI to explore model dynamics. The results are described in the next section.

IV. RESULTS

To give a first impression of the model and highlight general results we start with some illustrations of a typical run (for certain parameter conditions) and describe general results. Next we give an overview on indicators we measured. To exploit the first advantage of modeling, the availability of data, it is important which data is measured and compared. We then present the results from two parameter sweeps, and illustrate them in correlation tables. The data is processed with R [16].

A. Some general results and examples for output

We show examples of a run with the following parameter setting: endAt = 2000, howMany = 6, insistOut = 0.1, learning = 0.1, ModelSize = 40, topicQuantity = 0.2, social = 0.2.

Fig. 4 illustrates a sequence of messages during the model run. The upper line displays the topic, while the lower line refers to the respective participant speaking. It can be seen that participants talk about a topic for a couple of steps before switching to the next one. -1 is an error value which denotes that nobody was speaking at this time step. With a higher value of *insistOut* longer discussions on the same topic arise, because participants disagree more. The parameter *social* is also important for long speech sequences, because participants realign with the rest of the group.

Fig. 5 displays the share of possible topics, referring to the share of all topics available from participants substantive models that is already included in the group model. Fig. 5 shows a saturation curve, which is a robust result of CollAct. Hence, in such a discussion it should be carefully considered when to end. If it is stopped to early, interesting points may
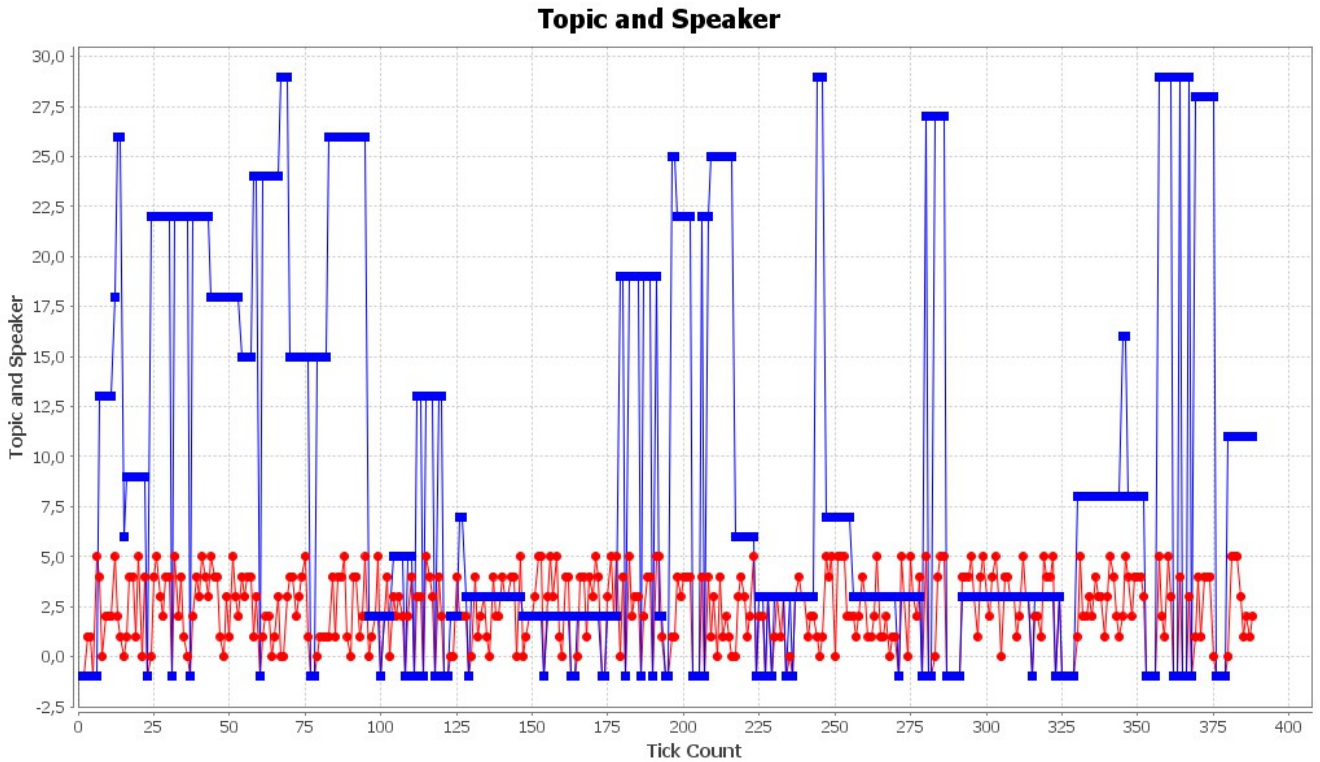
Fig 4. The first part of a run of CollAct. The upper line (blue) represents the topics,
while the lower line (red) refers to the speaking participant. As it can be seen, CollAct produces sequences of messages with
the same topic, sent from various speakers (participants).
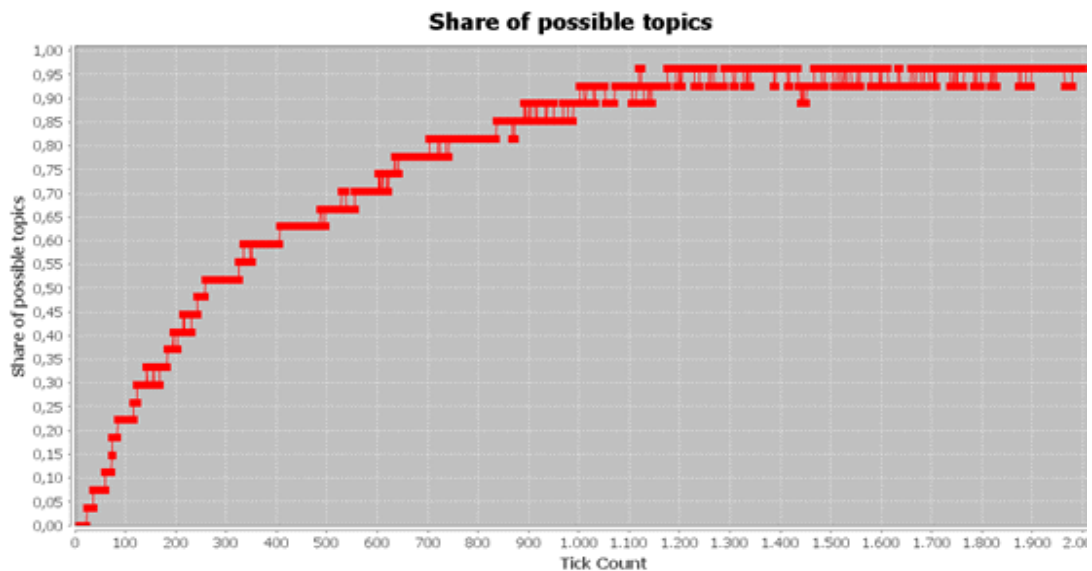
Fig 5. The share of possible topics (of all topics that are represented in the substantive models) in the group model

be overseen, while after a certain point none (or only marginal) additional information is included.

Fig. 6 display how roles change over time. To accomplish this the role value of participant X is looked up from every participant and summarized. This number is divided by the

6-vii
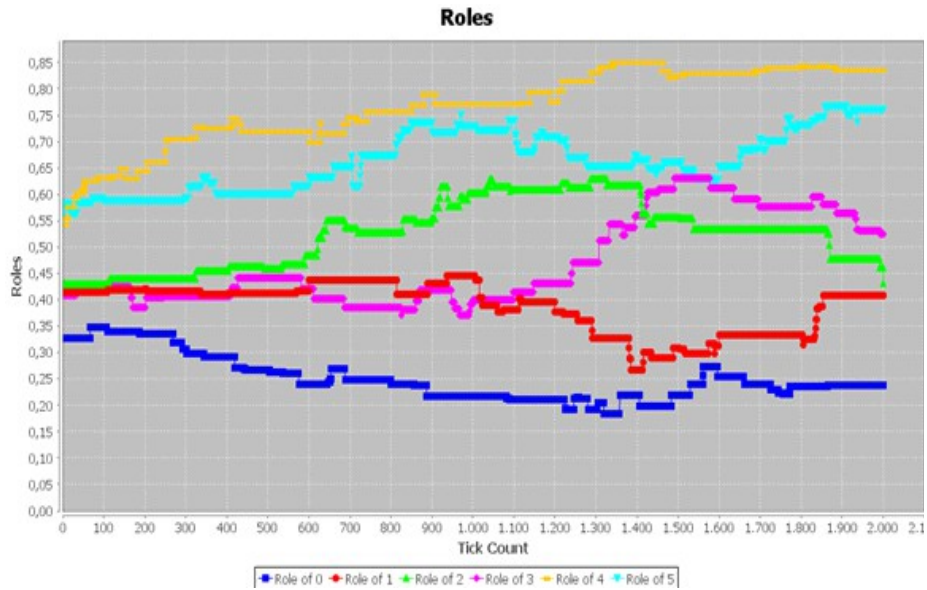
Fig 6. The progress of average roles over time with *insistOut* = 0.1
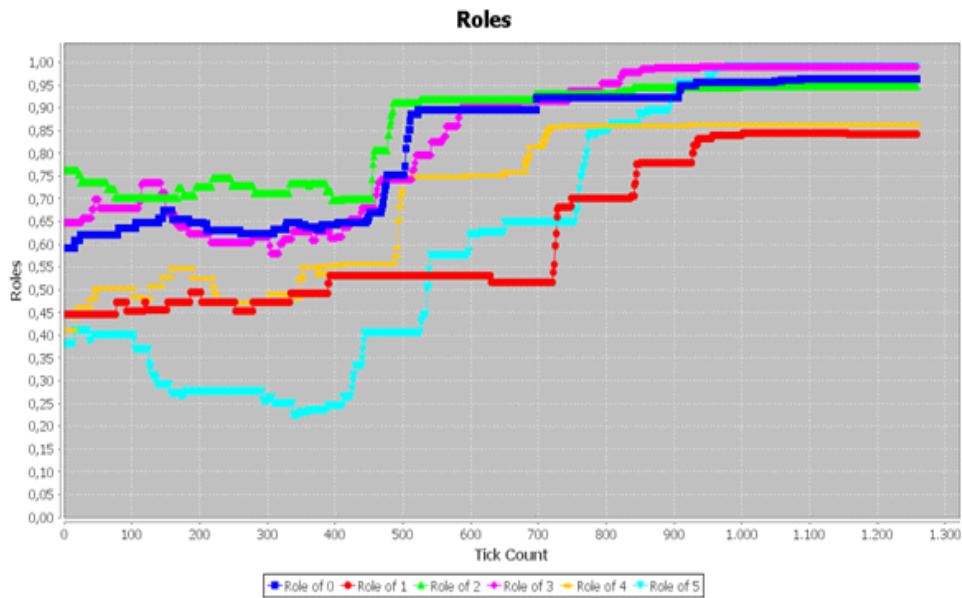
Fig 7. The progress of average roles over time with *insistOut* set to zero

number of participants, to gain the average perceived role of X. Fig. 6 illustrates strong change in roles. This observation raises the question if relational learning is implemented to strongly. Nevertheless, this might be realistic for participants who did not know each other before entering in a discussion. For fig. 7 we changed the value of *insistOut* to zero. This means that participants don't insist to take out topics that have already been included in the group model. In fig. 7, roles tend to become very positive and stabilize at a high level. Participants don't stick to conflicting topics and have a greater probability to talk about topics on which they agree,

rising the probability for learning in roles with a positive direction. This eventually leads to a high average role value.

B. Indicators

The results discussed before are of qualitative nature. Due to the high number of randomized decisions only typical patterns can be described. To evaluate CollAct in a quantitative way we needed indicators to measure and compare. Table III displays the indicators we chose. These are based on [7] and [17].

TABLE III.

INDICATORS

Time	Name	Description
Start	S_averageRole	average role value over all participants
	S_leadingRole	distance highest role to next role
	availableTopics	number of possible topics (listed in individual mental models) – this relates to cognitive diversity
	S_rangeRoles	range of roles
	averageTopicsPer-Participant	average number of topics per participant
End	substantiveLearning	change of averageTopicsPerParticipant
	rangeSpeech-Distribution	range of speech distribution (% of messages linked to a specific participant)
	rangeRoles	range of roles
	topicsInGM	number of topics in final group model
	leadingRole	distance highest role to next role
	averageRole	average role value over all participants
	tick	step count (length of model run may vary because of silence counter)

C. Parameter sweep and correlations

After setting indicators we conducted a parameter sweep to explore correlations of GUI parameters and output indicators. We used the Spearman rank correlation. We varied the following parameters:

```
howMany     2 – 10, step:1
social      0 – 0.8, step: 0.2
insistOut   0 – 0.8, step: 0.2
learning    0 – 0.8, step: 0.2
endAt       500, 1000, 1500
```

This parameter setting leads to 3375 variations, with which we simulated one run. Modelsize was set to 40, and topicQuantity to 0.2. Table IV presents a subset of the correlations identified for the results. To keep it well organized Table IV only displays the parameters and indicators with the highest correlations.

The highest influences are visible for *howMany* (the number of participants) and *availableTopics*. *AvailableTopics* indicates the number of available topics out of all substantive models of participants, and thus the two start indicators are highly dependent. However, the number of available topics, which also relates to cognitive diversity (how are topics distributed along participants) has a strong influence. Group size is known to have a strong influence [18], thus the reproduction of this with the model is a promising start. Some correlations are rather trivial, but still support the soundness of CollAct. E. g. *learning* leads to high substantive and relational (*averageRole*) learning.

The presence of a leading role at the beginning leads to a lower level of substantive learning. This may be due to one participant dominating the discussion, resulting in less possibilities to learn from diverse perspectives. Furthermore, a leading role at the beginning correlates with a lower average role at the end, which is interesting and may be due to the same mechanism discussed above.

InsistOut, which may be interpreted as a high level of controversy in the discussion, leads to a lower number of topics in the group model. Furthermore, a high level of controversy leads to a lower amount of substantive learning. Some claims in the literature see constructive conflict as a way to foster learning [19]. This may relate to the diversity of knowledge, which would match findings from CollAct, and not to the level of controversy as we use it here, which is about insisting to exclude others' opinions. A high level of controversy is correlated to a lower average role which confirms the qualitative finding for roles by checking the opposite direction (see section on general results). Interestingly, a high level of controversy also leads to a higher probability of a leading role at the end. This may be due to the lower average role: if all roles are lower, there is a higher probability of one single role rising above the others.

TABLE IV.

HIGHEST CORRELATIONS OF FIRST SWEEP

	insistOut	learning	howMany	availableTopics	Start_leadingRole
topicsInGM	-0.52	0.26	0.40	0.45	-0.17
substantiveLearning	-0.13	0.63	0.47	0.52	-0.17
averageRole	-0.34	0.61	0.34	0.33	-0.13
leadingRole	0.19	-0.15	-0.40	-0.38	0.38
rangeRoles	0.41	0.00	0.06	0.06	0.10
rangeSpeechPart	-0.10	0.02	-0.34	-0.31	0.18

To test our assumptions on these correlations we conducted another sweep with 5000 variations, setting the number of participants to 6. We varied parameters as follows:

```
social      0 – 0.9, step: 0.1
insistOut   0 – 0.9, step: 0.1
learning    0 – 0.9, step: 0.1
endAt       500- 1500, step: 250
```

Resulting correlations are displayed in fig. 8 (only those which have a value of at least 0.05 respectively -0.5). The second sweep underlines the findings of the first sweep. The influence of the amount of available topics, relating to cognitive diversity, is now corrected from the influence of a varying number of participants. Still it has a strong influence on the number of topics in the group model as well as on the substantive learning. The influence of the level of controversy of the discussion is even more obvious, emphasizing the previous findings. Furthermore the influence of *social* (Asch and halo effect) becomes visible. This was neglected in the first evaluation, because the influence of *social* seemed rather small compared to other factors. *Social* has a positive influence on the number of topics in the group model and on the average role value. Furthermore it hampers the rise of a leading role and the growth of a broad rang of roles.

The influence of a leading role at the beginning does not seem significant in the second sweep. It only correlates with indicators referring to the end situation of roles, which is rather trivial. The result that there is a strong influence of a leading role at start when the number of participants are varied presents an interesting point for further explorations.

	social	insistOut	learning	endAt	available Topics	average TopicsPer Participant	S_average Role	S_leading Role	S_range OfRoles
tick	0.05	0.07		0.95					
topicsInGM	0.15	-0.73	0.27	0.33	0.28	0.23			
substantiveLearning	0.07	-0.28	0.75	0.25	0.30	0.26	0.06		
averageRole	0.16	-0.43	0.71			0.08	0.28		
leadingRole	-0.10	0.23	-0.23				-0.08	0.18	0.07
rangeOfRoles	-0.15	0.46				-0.08	-0.14	0.08	0.22
rangeOfSpeechParticipation		-0.08	0.05	-0.14					0.06
availableTopics							0.72		
averageTopicsPerParticipant						0.72			
S_leadingRole									0.40

Correlations of input and output,
and input and input (parameters and indicators)

	tick	topics InGM	substantiv eLearning	average Role	leading Role	rangeOf Roles	rangeOf SpeechPar ticipation
tick		0.30	0.25				-0.14
topicsInGM	0.30		0.69	0.59	-0.25	-0.33	
substantiveLearning	0.25	0.69		0.78	-0.26	-0.16	
averageRole		0.59	0.78		-0.38	-0.41	0.05
leadingRole		-0.25	-0.26	-0.38		0.37	
rangeOfRoles		-0.33	-0.16	-0.41	0.37		
rangeOfSpeechParticipation	-0.14			0.05			

±(0.15 - 0.24)
±(0.25 - 0.34)
±(0.35 - 0.44)
±(0.45 - 0.54)
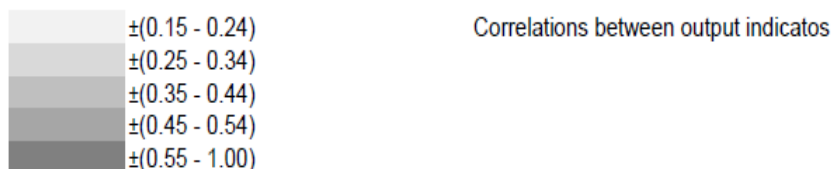±(0.55 - 1.00)

Correlations between output indicatos

Fig 8. All correlations from the second sweep which have a value of at least 0.05 respectively -0.05

6-x

V. Discussion

The decision for a complex cognitive model embraces some difficulties, because many design decisions are required and results may be difficult to interpret. Although there are good arguments to keep agent-based models simple, in some cases a more descriptive approach is reasonable [20]. Simulating micro-level relations among people who hold the knowledge in participatory processes might be important [21], as well as the interpretation of messages, the modeling of memory and path-dependency, and deliberation processes [15]. CollAct comprehends these points. Furthermore, we argue that in our case a complex cognitive model is reasonable, because a higher level of abstraction would absorb the processes we are interested in to model consensus building.

Because of the explorative character of our model the validation is not described in a separate section. While building CollAct we discussed in an expert round whether assumptions are realistic, and improved the model in an iterative way. The model has been tested for errors. While interpreting the results, some validation can be done "on the way": every reasonable result which is confirmed through empirical finding is a further little step for validation.

The significance of group size is also reflected on in empirical work [17], thus this result is a promising start. The level of controversy in the discussion presents another important influence, leading to a lower number of topics in the group model, a lower amount of substantive learning, and to a higher probability of a leading role at the end. With a low level of controversy roles tend to become very positive and stabilize at a high level. On the contrary, a high level of controversy is correlated to a lower average role.

The number of available topics, which also relates to cognitive diversity (how are topics distributed among participants) influences the number of topics in the group model as well as the substantive learning. *Social* (the probability for Asch and halo effect to occur) has a positive influence on the number of topics in the group model and on the average role value. Because participants tend to conform to topics they do not favor themselves, more topics can reach the necessary consent level to be included in the group model. Furthermore, it hampers the rise of a leading role and the growth of a broad range of roles. These are interesting findings for the function of (empirically proved) cognitive biases in group processes.

In the parameter sweep with a varying number of participants, a leading role at the beginning has a strong negative influence on substantive learning, and the average role at the end. This influence does not seem significant in the second sweep, were the number of participants was set to six. Hence, in CollAct the influence of a leading role at the beginning depends on group size.

Another, straight forward result is, that the integration of topics in the group model follows a saturation curve. Thus,

in such a discussion it should be carefully considered when to end.

VI. Conclusion and Outlook

CollAct presents a new approach to explore group dynamics via simulations. On the basis of the results presented some first conclusions about important influences in group discussions could be drawn. This was only possible with the integration of cognitive complexity. Especially the integration of substantive knowledge and relational knowledge and their interaction within the agent rules produce interesting dynamics, but also a large amount of data which has to be interpreted in an illustrative way. The results discussed in this paper are only a first start to demonstrate the scope of this model. These results will be further elaborated and backed up with empirical findings in future work. Thereby, the interrelation of a consensus, conformation, and the development of a shared understanding are central to our future model exploration. Shared understanding is a key aspect of many social learning theories (e.g., [7]), and consensus and shared understanding are not necessarily the same (see above). The influence of different role settings as well as different mental model combinations are subject of future research as well.

Possible extensions include topics which are assigned a negative opinion, to model conflict. Furthermore, learning in the substantive and relational models could be split up, e.g., to model situations were substantive learning takes place while participants know each other from previous meetings. Another possibility is to model agents heterogeneous in some attributes, e.g., *insistOut* or *social.* An important extension would be the integration of an active facilitator. At the same time such an extension would produce the need for further complexity.

Another interesting direction is the coupling with network theories to create larger learning communities, grown from the ground.

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7 PAPER IV: SOCIAL LEARNING IN AN AGENT-BASED MODEL: USING COGNITIVE BIASES TO SIMULATE LEARNING AND CONSENSUS FINDING IN GROUP DISCUSSIONS

Social learning in an agent-based model:
Using cognitive biases to simulate learning and consensus finding in group discussions

Geeske Scholz, Art Dewulf, and Claudia Pahl-Wostl

Abstract

The idea that group interaction can start social learning processes, fostering social change for sustainability, is appealing. However, analyzing factors that influence social learning is difficult, on the one hand because of context dependency, and on the other because internal changes in individuals are difficult to measure. Agent-based modeling provides a possibility of addressing these challenges and exploring the social dynamics occurring in group interactions. With CollAct (simulating **coll**aborative **act**ivities) we provide a model of group interaction which considers both cognitive and relational knowledge and learning. It is built around the question of how people gain a shared understanding and reach consensus in a group discussion. In the model, agents discuss an abstract issue, trying to reach a consensus. Agents have mental models, consisting of both substantive and relational knowledge. The linkage between own knowledge, interpretation of incoming messages and agents' contribution to the discussion is mediated by two social psychological processes: the Asch conformity effect and the halo effect. Results include an identification of factors influencing the number of topics included in the consensus and the amount of learning, and an exploration of the relationship between the building of a consensus and the development of a shared understanding. Two main conclusions of this exploration are that (i) high mutual esteem and the building of a shared understanding reinforce each other, and (ii) while high conformity and low controversy both foster consensus, cognitive learning is needed to build a shared understanding and to increase the support of a possible consensus.

Introduction

Social learning embraces many promises. It is expected to address the complexity of natural resource management, to foster behavioral change, and to promote collective action (e.g., Muro & Jeffrey 2008; Pahl-Wostl 2006; Stringer et al. 2006). The term social learning was coined by Albert Bandura (1977), who proposed a theory of learning via the imitation of role models, emphasizing the interaction between individuals and their social environment. Since then, the

idea of social learning has been developed further by various researchers (Muro & Jeffrey, 2008). Thereby, the building of a shared understanding is a crucial issue in social learning theories. But, how do people gain a shared understanding and reach consensus in an interactive group setting? This question is difficult to analyze within case studies, because internal changes of individuals are hard to measure. Only little knowledge exists about the social dynamics in the process of social learning (Sol et al. 2013). In this work, we explore the building of a shared understanding while agents try to reach a consensus in an agent-based model, called CollAct (simulating **coll**aborative **act**ivities). Thereby, consensus refers to a general agreement that might include aspects on which certain participants have doubts or disagreements but do not communicate them (for one reason or another).

We use a definition for social learning in Reed et al. (2010), supplemented by Scholz et al. (2013). Accordingly, social learning occurs if: (i) a change in understanding has taken place in the individuals involved; (ii) this change goes beyond the individual and becomes situated within wider social units or communities of practice; (iii) this change occurs through social interactions and processes between actors within a social network; and (iv) convergent learning takes place, referring to an increase in shared understanding (Reed et al. 2010; Scholz et al. 2013). To measure whether or not social learning took place, Scholz et al. (2013) propose the following indicators: (i) change in mental models (substantive and relational); (ii) impact of substantive and relational outcomes in the wider context, and (iii) increased similarity between mental models. Our model focuses on how social learning can be facilitated through social interaction in groups. Thus, we leave the second indicator, the impact of substantive and relational outcomes in the wider context, for further research. Accordingly, we are interested in the change in mental models and an increased similarity between mental models. Thereby, mental models refer to personal internal representations of the surrounding world.

During group interaction social influences must be taken into account. Conformity, referring to participants trying to align to some social norm, or the (supposed) 'group opinion', is an important driver for group dynamics (Baron & Kerr 2003). Another important driver, which may have negative impacts on group processes and the outcomes of group interaction (in example participatory processes), are power relations (Kothari 2001; Stringer et al. 2006). We consider these factors in CollAct through the implementation of cognitive biases. We consider cognitive and relational aspects, and as influences, conformity and relational aspects, including power and sympathy. CollAct allows the exploration of group dynamics, by asking such questions as: When do individual views on a problem converge into a shared understanding?; how do individual and group properties interrelate; how do roles shift and emerge?; and how is consensus composed of individual perspectives?. The results of an exploration with CollAct can then be interpreted back to reality, and compared to empirical research.

CollAct is designed as a complex cognitive model for exploration, thus it includes several assumptions and unknown parameters. While this is challenging and results should be handled with care, there are arguments in the literature that call for such a complex model: Conte and

Paolucci (2001) point out the need to include cognitive reasoning (e.g., knowledge comparison and knowledge about other agents) to go beyond social contagion and simulate "intelligent social learning". Barreteau and Le Page (2011) describe the chances of including the micro level processes of knowledge construction within collaborative settings to explore the dynamics occurring in participatory research. Troitzsch (2012) proposes that for simulating communication and interpretation during interaction, the interpretation of messages, memory, and deliberation processes should be considered. All of the above processes are considered within CollAct.

This article begins with a description of the theoretical background CollAct builds upon. We then describe the conceptual model and some implementation details. The next section presents the results of simulation experiments: General model behavior, correlations, and an analysis of consensus and the building of a shared understanding. We end with a discussion, concluding remarks, and an outlook. In addition to this article, a runnable version of CollAct is placed in the [CoMSES Net Computational Model Library](#) and can be found at https://www.open-abm.org/model/4255/version/1/view .

Theoretical background

We base our model on a framework that has been developed for the analysis of social learning facilitated by participatory methods (Scholz et al. 2013). This framework is tailored to the application of the analysis of participatory methods at the group level, thus, it is well suited for serving as a conceptualization of group interaction in a discussion. Our interpretation of it (adapted to our needs) is displayed in Figure 1.

A core component in this framework is the mental model concept, referring to personal internal representations of the surrounding world. The mental model concept can be traced back to Kenneth Craik (1943), who was the first to propose the idea that people have a 'small-scale model' of external reality in their head. Since then, mental models have been discussed in many disciplines (Johnson-Laird 1983; Jones et al. 2011; Kolkman 2005; Norman 1983). Nevertheless, further research into the relationship between individual and collective mental models, referring to the degree of shared understanding among a group of people, is still needed (Jones et al. 2011).

Mental models determine how one observes the world. As a result, they define the relationship to the environment. This aspect of mental models is used for CollAct. Every participant has a mental model. Mental models consist of two 'sub-models': the substantive model, which includes knowledge about the topic at hand, and the relational model, including knowledge about other actors (e.g., personal characteristics) and self-perception. By illustrating these two components it is possible to simulate cognitive and relational learning. Furthermore, by including a substantive and a relational model, individual characteristics, influences, and interpretations on the factual level and influences and interpretations on the relational level are grasped.
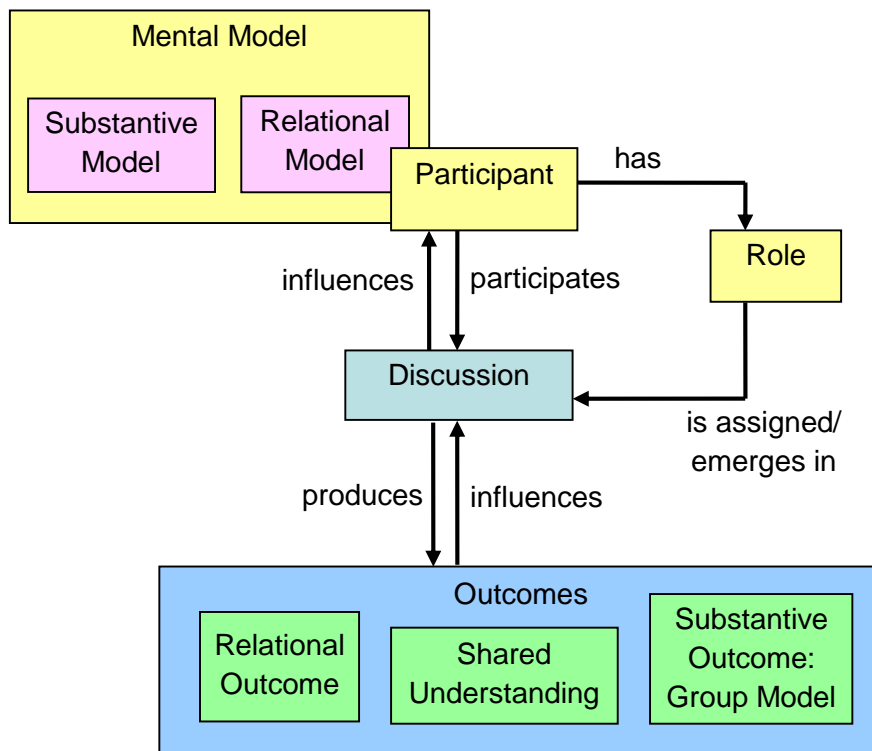
Fig. 1: Conceptual framework underlying CollAct (based on Scholz et al. 2013)

In CollAct, participants interact in a discussion. All of them have a certain role within this discussion (comprehending, e.g., the level of involvement). Furthermore, every participant has a perception of the other participants and a self-perception, referred to as relational model. Roles on group level can shift and emerge through the change of relational models at the individual level. In addition to the relational model, participants have a substantive model, including topics they perceive to be important for the issue at hand. Substantive models influence the content of the discussion. In both relational and substantive models learning can take place, influenced through interaction within the discussion. Outcomes of discussion include relational outcomes (such as better/worse relationships) and substantive outcomes. A consensus is a substantive outcome, modeled as *group model* in CollAct. Furthermore, a shared understanding can emerge, referring to an increased overlap in the mental models of participants. The elements of the framework are described in Table 1.

Table 1: Description of elements (based on Scholz et al., 2013)

Element	Description
Discussion	The discussion provides the social interaction context, leading to specific outcomes. Because we use group model building as inspiration, the substantive outcome is called group model. The group model at ending time may be seen as consensus. Outcomes produce a feedback to the discussion in which actors interact.
Participant	Participants are all stakeholders interacting in a discussion. Every participant has a role and a mental model.
Mental model	Mental model comprises a substantive model (e.g., perceived state of the environmental system and relevant causalities) and a relational model (representation of other actors, including representations of personal characteristics, skills, preferences, and knowledge).
Role	Participants can take on roles based on their function (e.g., convener). Other roles (e.g., leader and facilitator) can emerge during a process. Following this, roles may exist prior to a participatory method or emerge during the process. Furthermore, aspects of roles can change through engagement or through attribution by other participants. The emergence or shift of roles at the group level is based on changes in the relational models of actors.
Relational outcome	Relational outcome refers to outcomes associated with actors' relationships. An example is the creation of trust. Relational outcomes can support or hamper the further development of the process.
Shared understanding	Shared understanding refers to the convergence in mental models of participants. Interactions may possibly lead to convergent conceptual change and a shared understanding of the topic, presenting a convergent direction of learning. A convergence in learning means that participants integrate concepts (and eventually perspectives) gleaned from one another and/or develop new, shared concepts.
Substantive outcome	The group model produced in CollAct is a substantive outcome. Further substantive outcomes of action situations include actions, rules, and knowledge. Of these, knowledge and rules can impact back on the action situation.

To link these elements through processes, we employed findings from cognitive learning research and two cognitive biases, explained in the following. For learning (change in mental models) we take the following findings as a theoretical background: (i) The confrontation with new knowledge can lead to a change in concepts (Anderson 2000); (ii) people develop concepts quickly on little evidence, and tend to stick to these concepts without strong evidence against them (Dörner 1999); and (iii) people tend to search for information that supports their assumptions (Confirmation Bias) (Plous 1993).

The interpretation of messages, and the resulting decisions to learn and/or send a message, are modeled to be influenced through two cognitive biases: The Asch and the halo effect. Both of them are empirically proven and of specific interest for linking the knowledge represented in relational models to the perception and decision processes of agents. The Asch effect (Asch 1951) describes how people confirm to wrong judgments under perceived group pressure. We use it to model conformity. The halo effect halo effect (Thorndike 1920) describes how a positive judgment of a person in one dimension (e.g., good looking) creates a positive bias in the

judgment of this person on another dimension (e.g., competent). We use the halo effect to include the knowledge of the relational models of agents in the decision process.

The model CollAct

Agents in CollAct, modeled as *participants*, discuss an abstract issue, trying to reach a consensus. Topics can be included in the *group model* if sufficient supportive messages occurred. Messages are exchanged between participants via their roles and *discussion*. Discussion provides the virtual 'room'. The discussion takes place in a turn-taking manner, per time step only one message is 'heard' by all participants. No facilitation or moderation is included, the class *facilitator* is passive, handling entrances in the group model. The discussion in CollAct proceeds until either a sufficiently long period of silence occurs (20 steps per default), or time is over (this can be set as parameter in the GUI). Figure 2 displays an overview of classes. Probably the most interesting thing about CollAct is the explicit modeling of the mental models of the participants, comprehending both a substantive and a relational model. In both of these models learning can take place, and both are used to interpret incoming messages and decide upon further actions (messages).

CollAct is implemented in Repast Simphony (North et al. 2013). In the following, we present all the classes of CollAct including their main functions, all included parameters, and some remarks on validation. The description of CollAct and the qualitative results are based upon a conference proceeding (see Scholz et al. forthcoming).
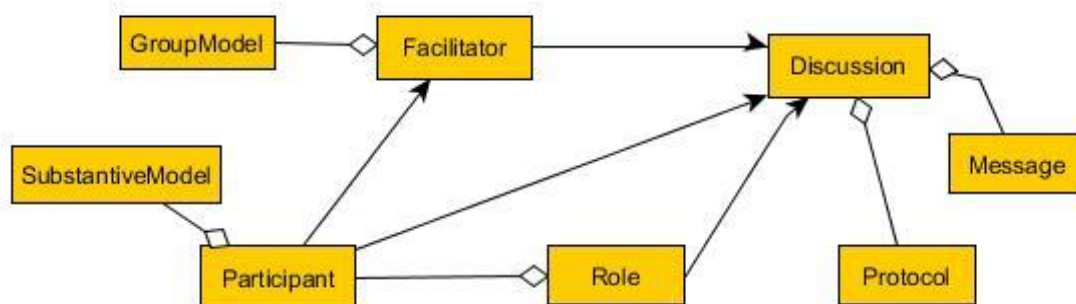
Fig. 2: Class diagram with main relations

Model

Instances of the class model are used to represent participants' substantive models and the group model. This allows the easy comparison of both at the end of a simulation run for evaluation purposes. The group model represents the emerging consensus of the group, and is held by the facilitator. The class model includes a simple array of a predefined size, in which topics can be saved. Every field in this array refers to a specific topic. A 1 in array fields X means that the participant has topic X in her substantive model, respectively that topic X is included in the

group model. A 0 means that topic X is not included. The group model changes if new topics are included or removed. The same applies for participants' substantive models, which can change through learning. An example of an emerging group model is presented below. The model offers methods for checking if a certain topic is included, to add and remove topics, to get the number of included topics, and to get a random topic included in the model.

Group model development:

1. 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0
2. 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0
3. 0 1 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0
4. 0 1 0 1 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0
5. ...

Facilitator

The facilitator has no active part besides managing the group model (in the current version - this may be changed in future implementations). The facilitator provides information about the current status of the group model, and adds new topics if a certain consent level is reached. This consent level is set to the number of participants per default. In our implementation not all participants have to agree on a topic to be included, because the facilitator sums up all messages in favor of and against topics. Topics can be removed again, if the consent on a topic falls 2 below the consent level.

The facilitator has a method for checking whether a topic is included in the group model, and provides methods for the graphical display of model results and end routines for evaluation.

Participant

Participant is the core class of CollAct. As in the theoretical framework CollAct builds upon, participants' mental models are split into a substantive and a relational model. The substantive model is saved as an instance from the class *model* (see above), while the relational model is saved as part of a *role*. Every participant has a role. Participants interpret the last message of the discussion concerning the content (is the topic included in their own substantive model?) and the speaker (how is this speaker perceived?). On the basis of this interpretation, participants are able to learn (update their own substantive and relational model) and decide on further actions. To be able to learn, participants have an update method. Learning in the relational model is influenced by the similarity of opinions (if the topic proposed from participant A is also included in the substantive model of participant B). Learning in the substantive model is influenced by the perception of the speaker. Possible actions are implemented in an *options* method. The options method is implemented as decision tree. This decision tree is displayed in Figure 3. Thereby, the ovals are possible actions. Participants can (i) propose to include the topic of the last message in the group model; (ii) propose to not include this topic; (iii) speak along (to whatever the previous speaker said); (iv) or change the topic. The rectangles represent decisions

on the way to a possible action. For these decisions, some of the values used have been calculated by the *interpret* method: content and person. Others, like *social* and *insistOut* are parameters which can be chosen in the GUI at the beginning (for a complete list of parameters see Table 2). The values for Asch and halo are calculated by asking how many other actors wanted to include a topic (request is sent to *discussion*), respectively by looking at the role value of the speaker, which is returned by the interpret method in the form of person. As an example, a way through the decision tree could be: The last message had a topic not included in the group model so far. The content is not interesting for participant A (interest is lower than a random number). Nevertheless, A is *social*, and the Asch effect is higher than a random number, and higher than the probability for the halo effect to occur. Thus, participant A conforms to the perceived group opinion and agrees to include the topic.
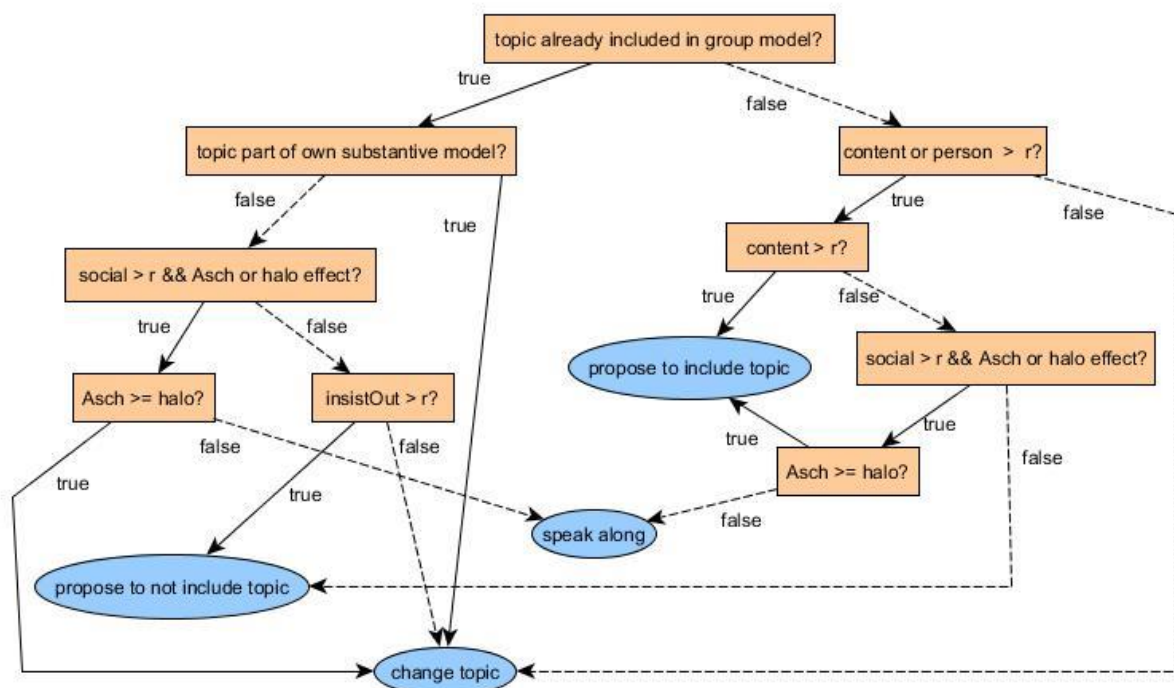
Fig. 3: Decision tree in the *options* method of *participant* (Scholz et al. forthcoming, p.4)

To keep Figure 3 clear, we did not include the decision process for changing the topic. The change of topic is implemented in another decision tree, which is shown below in pseudo code.

```
pt = most likely topic from the protocol
p, pm = parameter (see Table 2)
        If (pt is included in own mental model and pm > random)
                propose pt
        Else if (p > random) propose to exclude pt
        Else propose new random topic of own mental model
```

If a participant decides to speak (send a message), the produced message is passed to the participant's role. The final decision, whether or not the participant tries to speak the next round, is taken in her role.

Message

The class *message* is used to model the inputs of participants to the discussion. Messages are tuples (speaker, topic, in) (based on Troitzsch 2012) *Speaker* identifies the participant who sent the message, *topic* is a number and identifies the topic the participant talks about, and *in* is a Boolean value that indicates if the participant wants to include or exclude this topic from the group model. Additionally, the class message provides methods for returning the value of each element (e.g., speaker).

Role

A role belongs to a participant. The role includes the relational model of this participant, including the perception of other participants and self-perception. Thus, the class *role* could also be seen as 'perceived role' of a participant, while roles on the group level emerge out of all 'perceived roles' of participants included in a discussion. The information of the relational model is used within *participant* (see above). Furthermore, it enforces or weakens the speech probability. The class *role* provides a method named *speak* that is called up by participant. Next, *role* increases or decreases the probability of the message being passed on, depending on the perceived position of the participant in the discussion: If a participant sees herself in a strong position (high role value compared to the rest of the group), the speech probability rises. If she sees herself in a weak position, the probability decreases. Role then evaluates if the probability is high enough (by comparing it to a random number), and if so, calls up the speak method of discussion to register the message for the next step.

The values saved within the relational model are an aggregate of various dimensions (such as sympathy, competence, and power), and are presented as real numbers between zero and one, one being the most positive and zero the most negative value. An example for a relational model is displayed below:

Participant 0 has an average group perception of 0.60:

- 0 is seen as 0.34 (self-perception)
- 1 is seen as 0.46
- 2 is seen as 0.37
- 3 is seen as 0.89
- 4 is seen as 0.68
- 5 is seen as 0.87

In this example, participant 0 sees herself in a weak position within the group, hence, the speaking probability of 0 is decreased.

Discussion

The class *discussion* represents the virtual room. All participants and the facilitator know their discussion, and can call up a method of discussion to 'hear' the last spoken message. Furthermore, participants can pass a message to discussion via their role, registering the wish to take part in the conversation by sending a message. To realize a turn-taking conversation, only one registered message per step is chosen by discussion to be spoken out 'aloud'. At the moment, this decision is taken randomly. Discussion saves the chosen messages in a protocol, providing a shared memory of the most recent messages. Additionally, discussion provides end routines for the model evaluation.

Protocol

The class *protocol* is used by *discussion* to store messages. It saves the last n (this depends on the parameter *forget*, which is set on 3 per default) messages with different topics in a consecutive order.

Furthermore, it saves n possible occurrences for each different topic. When a new entrance is added, protocol restructures. Figure 4 displays the structure of protocol and a restructuring event. On the left side of Figure 4, the most recent message was on topic B. Furthermore, there was already one more occurrence of a message with topic B in the recent discussion. Before B was the topic of the discussion, participants talked about C, and before that, about A. In the next step a new message is chosen, which is on topic A. The protocol restructures, now saving A as the most recent topic (with four occurrences in the recent discussion), followed by B, and so on. Through protocol a path-dependency of the discussion is realized.

The class *protocol* provides a method which returns the most probable topic to speak about (with respect to the protocol). Thereby the probability for a topic to be chosen depends on its location in the protocol (higher for more recent topics) and its number of entrances. Furthermore, protocol provides a method that returns how many different actors wanted to include a certain topic, which is used to calculate the Asch effect. Thereby, the highest possible number depends on the number of possible entrances in protocol (*forget*).

SessionBuilder

SessionBuilder is a class required to run a Repast Simphony model (North et al. 2013). *SessionBuilder* manages the simulation by reading in parameters from the GUI, instantiating the other objects, and placing them in a context.
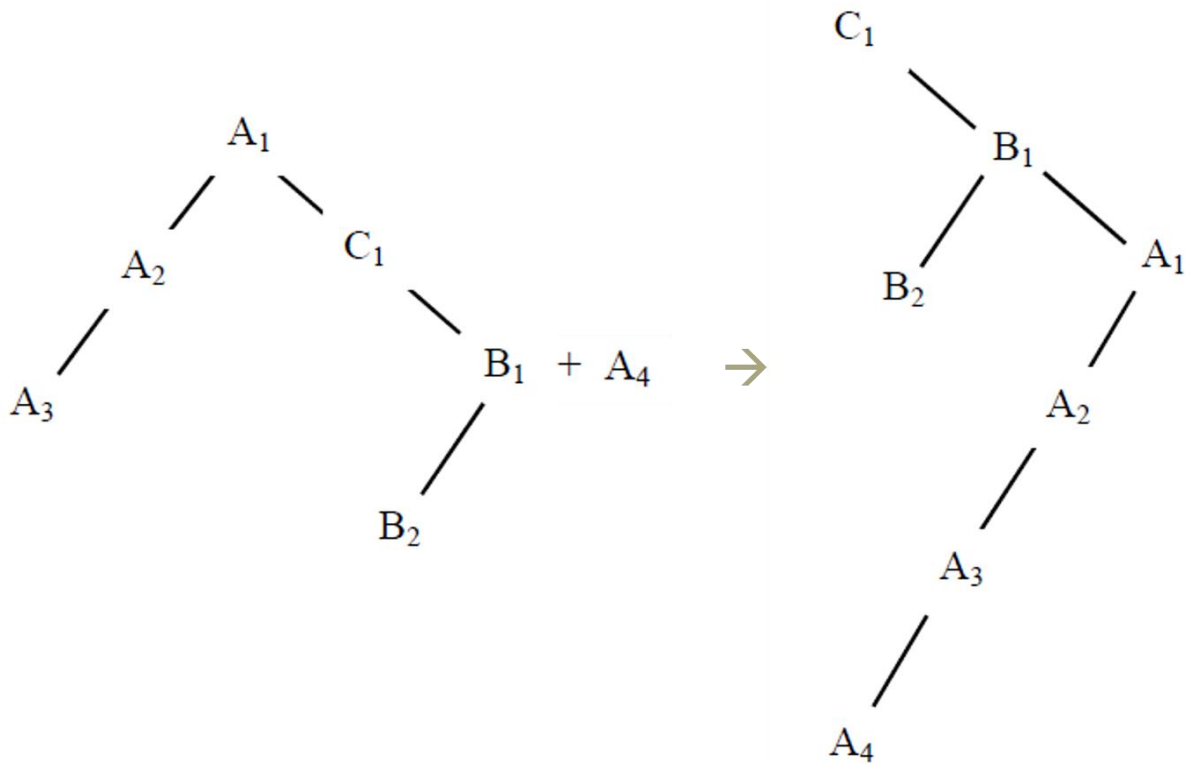
Fig. 4: The implementation of protocol with a forget value of 4, ensuring path-dependency in the discussion

Parameters

We tried to keep the number of parameters as low as possible, and reduced them in several iterations. At the moment, CollAct uses 14 different parameters, which are listed in Table 2. Unfortunately, parameters could not be set on the basis of empirical evidence. Empirical evidence is not sufficient to estimate parameters for learning models (Brenner 2006). However, CollAct is an explorative model, aimed at illustrating basic dynamics. Hence, we try to use parameters that approximate the real values and conducted parameter sweeps to estimate the influence of parameter changes.

Further uncertainties in CollAct include the consent level, which is set to the number of participants, and the choice that evidence against concepts has to be ten times stronger to take them out as the evidence needed to include new concepts (in update). The latter is a conceptualization of the finding that people develop concepts quickly on little evidence, and tend to stick to these concepts without strong evidence against them (Dörner 1999).

Table 2: Parameters of CollAct

	Name	Description	Default value
GUI parameters	howMany	Number of participants	6
	ModelSize	Capacity of substantive models	40
	topicQuantity	To what extend are mental models of participants filled (randomly)	0.2
	social	Probability for Halo and Asch effect	0.2
	insistOut	Probability of insisting on the exclusion of certain topics out of the group model again	0
	learning	Probability of learning	0.1
	endAt	Stopping time (end of session)	500
	forget	Gives the amount of memory capacity for speech acts	3
	freqProb	Multiplier for frequency of a topic (in ProtocolItem, inner class of Protocol)	0.3
	pm	probability of joining a topic also represented in myModel	0.3
	p	probability of bringing in a topic not represented in myModel from the protocol (to be not included in the group model)	0.05
	openness	Openness to topics not included in myModel	0.3
	silenceStop	After this number of steps without a speech, CollAct is stopped	20
	k	Proportionality constant for logistic growth function for roleMapping update (learning)	0.5

Validation

Because of the explorative character of CollAct, an explicit validation besides expert feedback is difficult. During the implementation phase of CollAct we added model parts stepwise: We started with a basic discussion model, then added mental models, and integrated roles, cognitive biases, and learning. This process allowed the testing of the smaller model versions by comparing the model results to the expected results. Furthermore, this process was accompanied by intense discussions of underlying concepts and results.

Two other steps for validation were taken while evaluating CollAct: All correlations found during parameter sweeps were (i) intensively discussed for if they 'make sense', and (ii) compared to empirical research wherever possible. Results of this endeavor are presented in the next section on simulations and the discussion.

Simulations

We start our presentation of simulation results with some overall results and output examples, to give an impression of CollAct. Next, we discuss correlations found through two parameter sweeps. In the last part of this section, we discuss consensus versus the building of a shared understanding, presenting results of a third, narrower, parameter sweep.

Some overall results and examples for output

CollAct simulates discussions with successional clusters of messages on the same topic. Figure 5 shows an example of a run, where 6 participants talk about different topics. It can be seen that different participants talk about the same topic for several steps.

While participants discuss with each other the inclusion of topics in the group model, they can learn about new topics, and learn about each other. Figures 6 and 7 show how roles shift over the simulation run. In these figures, roles are aggregated as follows: The values of the relational models of all participants for participant X are summarized and then divided by the number of participants. This procedure allows the calculation of the 'overall' role of a participant in the discussion.

As can be seen in Figures 6 and 7, the parameter insistOut influences the progress of roles. When insistOut is set to zero, roles tend to become very positive. When insistOut is higher, participants 'argue' with each other. The discussion is controversial. Thus, the possibility is higher that 'negative learning' takes place, meaning that participants lower the perception of one another because they notice that they have differing opinions.

Another straight forward finding is that the integration of topics into the group model in CollAct follows a saturation curve.
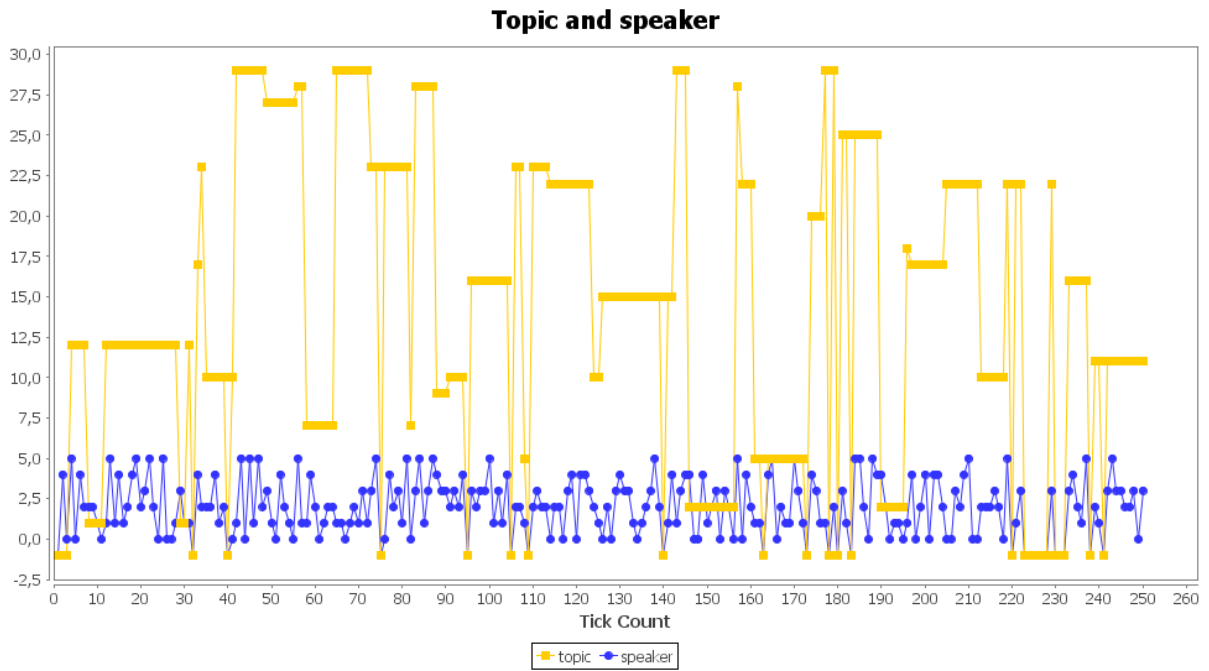
Fig. 5: Participants 0 - 5 (speaker) talk about different topics (topic). -1 indicates that nobody is speaking at this time step.
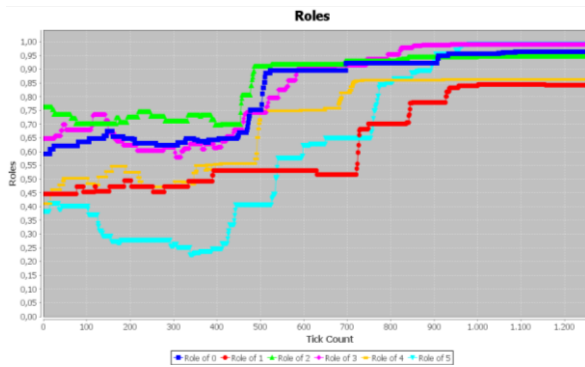
Figs. 6 and 7: The progress of roles over the simulation run. For the left figure insistOut is set to zero, while in the right figure insistOut has a value of 0.1 (Scholz et al., forthcoming, p.7)

Indicators and main correlations

To be able to explore model dynamics, we introduce a set of indicators, presented in Table 3. These indicators are used to produce data with two parameter sweeps.

Table 3: Indicators chosen to evaluate CollAct

Time	Name	Computation	Reflects/indicates
Beginning	S_averageRole	Average role value over all participants	Mutual esteem at the beginning
	S_leadingRole	Distance of highest role to next role	If a leadership exists at the beginning
	availableTopics	Number of possible topics (listed in individual mental models)	Cognitive diversity. This indicator is highly correlated to *averageTopicsPerParticipant*, but adds the information how topics are spread over participants
	S_rangeRoles	Range of roles	How homogenous/heterogeneous roles are spread over participants at the beginning
	averageTopicsPer-Participant	Average number of topics per participant at the beginning	How many topics are included in the substantive models of participants at the beginning
End	substantiveLearning	Average topics per participant at the end	How many topics are included in the substantive models of participants at the end of the simulation. Reflects the amount of substantive learning if contrasted with *averageTopicsPerParticipant*
	rangeSpeech Distribution	Range of speech distribution (% of speech acts linked to a specific participant)	How equal/unequal is the amount of participation in the discussion
	rangeRoles	Range of roles	How homogenous/heterogeneous are roles spread over participants at the end
	topicsInGM	Number of topics in final group model	Complexity or broadness of final group model
	leadingRole	Distance of highest role to next role	If a leadership has stabilized/emerged during the simulation
	averageRole	Average role value over all participants	Mutual esteem at the end
	Tick	Step count (length of model run may vary because of silence counter)	Length of the simulation run

After identifying indicators we conducted a parameter sweep to explore the correlations of GUI parameters and output indicators. Results were summarized and handled using R (R Development Core Team 2013). We varied the following parameters:

- howMany 2 – 10, step:1
- social 0 – 0.8, step: 0.2
- insistOut 0 – 0.8, step: 0.2
- learning 0 – 0.8, step: 0.2
- endAt 500, 1000, 1500

This parameter setting results in 3375 variations, of which each was simulated for one run. To identify correlations we used the Spearman rank correlation coefficient. For the first sweep, the

highest correlations are found for *howMany* – the number of participants. The highest correlations for *howMany* are displayed in Table 4. The significance of the group size is known to have a strong influence in empirical research (Baron & Kerr 2003), thus, this is a promising start.

Table 4: Highest correlations for *howMany* (first parameter sweep)

	topicsInGM	substantive-Learning	avera-geRole	leadingRole	rangeSpee-chPart
howMany	0.40	0.47	0.34	-0.40	-0.34

We further tested the hypothesis that that homogenous and smaller groups speed up decision processes, as described in empirical research (Irvin & Stansbury 2004). This is also supported through correlations produced by CollAct, although these correlations are not very high (see Table 5).

Table 5: Correlations of *howMany* and *availableTopics* with the length of simulation runs

	tick
howMany	0.09
availableTopics	0.09

While this is a promising start, *howMany* also highly correlates with the other indicators. Thus, we conducted another parameter sweep where we set the number of participants to six to explore the other correlations (Scholz et al., forthcoming). We varied parameters as follows:

- social 0 – 0.9, step: 0.1
- insistOut 0 – 0.9, step: 0.1
- learning 0 – 0.9, step: 0.1
- endAt 500- 1500, step: 250

Some rather trivial correlations found are the influence of the parameter *learning* on the amount of substantive learning and changes in role indicators. Furthermore, start and end indicators that indicate the same characteristic at two different model times correlate (such as *S_averageRole* and *averageRole*). These correlations were also used for further testing if CollAct works how it is intended to do.

The influence of the amount of available topics, relating to cognitive diversity and the amount of knowledge, correlates with the number of topics in the group model as well as with the

substantive learning. This is due to the higher number of topics available for both inclusion in the group model and mutual learning.

The level of controversy of the discussion (*insistOut*) has a negative influence on the number of topics included in the group model. If participants argue about topics, they have less time to include other topics, and tend to remove more topics from the group model. Furthermore, the level of controversy has a negative influence on the average role (see qualitative findings discussed above). If the average role is low, there is a greater chance of a broad range of roles, thus the level of controversy also influences the range of roles and the possibility of a leading role.

Social (Asch and halo effect) has a positive influence on the number of topics in the group model and on the average role value. This is because participants conform to topics they do not 'really' support, and avoid conflict which could lead to negative relational learning (decreasing average role). Additionally, *social* hampers the rise of a leading role and the growth of a broad range of roles. Controversy and conformity are linked in reality, because a low level of controversy actually could stem from conformity. However, in CollAct both influences are modeled independently, allowing for a more detailed analysis.

In summary, the following factors have an important influence on the number of topics included in the consensus and on the amount of learning that takes place in CollAct:
- The group size;
- The level of controversy within the discussion;
- Available knowledge and cognitive diversity; and
- Conformity in form of cognitive biases (Asch and halo effect).

Consensus versus shared understanding
To analyze the building of a shared understanding compared to the reaching of a consensus, we defined two more indicators: Group model support and shared understanding.

Group model support:

This refers to the percentage of topics in the group model that would have a majority regarding participants' substantive models.

Shared understanding:

Shared understanding is implemented as the number of topics which would have a majority concerning participants' substantive models (at least 50 % of all participants have these topics in their substantive models).

An example of why these indicators and the following exploration are interesting is displayed in Figure 8. There, we present a comparison of the share of possible topics (of all available

topics) included in the group model and the average support for each topic included in the group model. In the displayed run, the share of possible topics included in the group model increases throughout the simulation, while the support for this group model increases at first, and after an early peak, slowly decreases. This means that there are also topics included that do not have a 'true' majority. Hence, it is important to keep track of the support for developed group model. To explore this issue further, we conducted another, narrower parameter sweep including the newly introduced parameters.
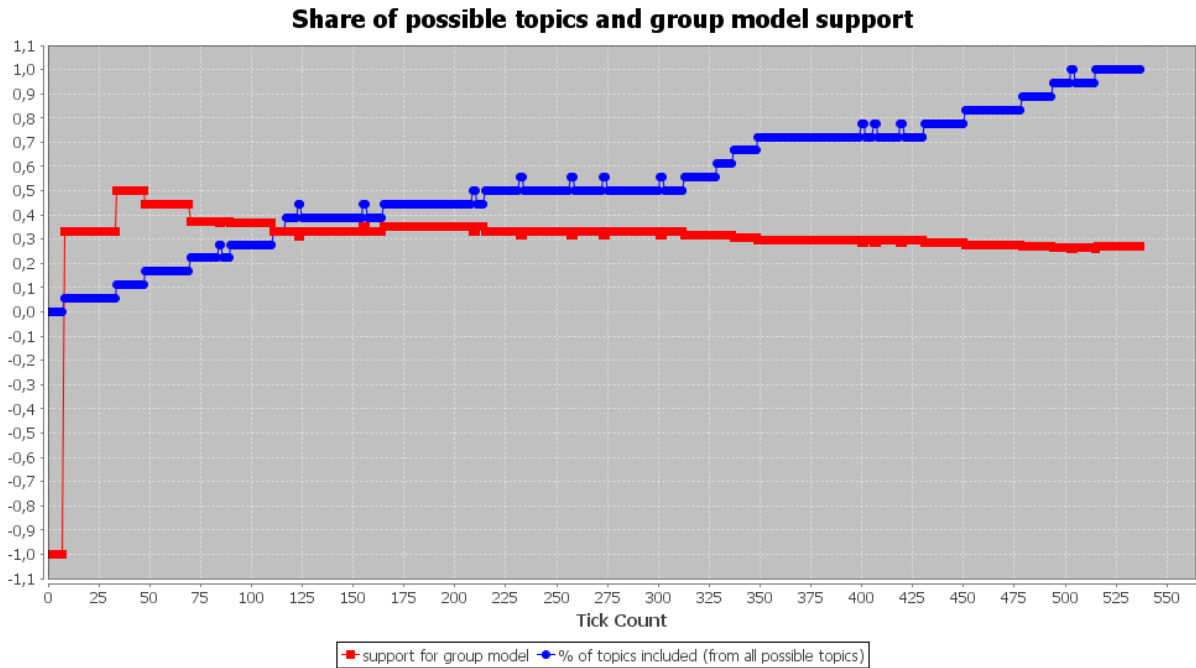
Fig. 8: Example run of the comparison of the share of possible topics (of all available topics) included in the group model and the average support for each topic included in the group model. -1 indicates that no topic is included in the group model so far.

The first two parameter sweeps indicated the significant influence of learning, which is a sensitive parameter that may be implemented too strongly. We therefore limited the influence of learning, and chose a setting that seemed most realistic, including the following parameters:

howMany = 6; topicQuantity = 0,2; modelSize = 40; and endAt being constant at 250

- social 0 - 0,5; steps 0,05
- insistOut 0 - 0,5; steps 0,05
- learning 0 – 0,1; steps 0,05

We simulated each parameter combination 10 times, resulting in 3630 runs.

The stopping time of 250 steps (possible speech occurrences) can be compared to a 2-3 hours discussion session. As a result of the chosen stopping time, the silence counter was never used, thus the discussion was always 'interrupted' for time reasons. The short time enforces trade-

offs between consensus finding and the representation of the 'true' consensus in the form of the shared understanding participants possess. Table 6 displays the correlations for this third sweep. The results can be grouped around two main findings, which are discussed below. For this reason the correlation table is also divided in two parts.

Table 6: Spearman correlation of parameters and indicators for the third sweep (*=double entry or self-correlation, these have been taken out for clarity). Only correlations higher than +/- 0.05 are displayed.

	social	insist-Out	learning	topics-InGM	average Topics-pP	GM-support	shared-Understanding	availa-ble-Topics
topicsInGM	0.24	-0.58	0.16	*	*	*	*	*
GMsupport	-0.08	0.13	0.66	-0.05	0.69	*	*	*
sharedUnderstanding			0.6	0.21	0.66	0.77	*	*
availableTopics					0.54	0.07	0.08	*
S_averageTopicspP				0.2	0.75	0.32	0.32	0.7
averageTopicspP		-0.05	0.59	0.29	*	*	*	*

	learning	topics-InGM	average Topics-pP	GM-support	shared-Understanding	average Role	leading-Role	range-Roles	range-Speech-Partici-pation	S_lead-ingRole
S_averageRole		-0.05	0.08	0.13	0.09	0.95				*
S_leadingRole							0.76	0.35		*
S_rangeRoles							0.37	0.91	0.05	0.39
averageRole	0.16		0.21	0.25	0.21	*	*	*	*	*
leadingRole							*	*	*	*
rangeRoles	0.1		0.06	0.08	0.09		0.41	*	*	*

The first set of findings is related to cognitive learning and the contents of the group model. For this we used the upper half of Table 7. As can be seen, high conformity (*social*) and low controversy (*insistOut*) both foster a broad consensus (high number of topics in the group model). These correlations are also displayed in Figure 9.

However, conformity and controversy do not correlate significantly with the amount of shared understanding. Furthermore, the group model support decreases with higher conformity, while it increases with a higher controversy of the discussion. This is due to the inclusion of topics in the group model that do not have a 'true' majority.

On the other hand, *learning* has a strong positive influence on the support of the consensus and on the shared understanding among participants. Figures 10 and 11 display the influence of learning on the building of a shared understanding and on the support for the group model. Thus, in CollAct substantive (cognitive) learning is needed to build a shared understanding, while conformity and relational influences are sufficient to agree upon a 'consensus' that is not truly supported by a majority of participants.
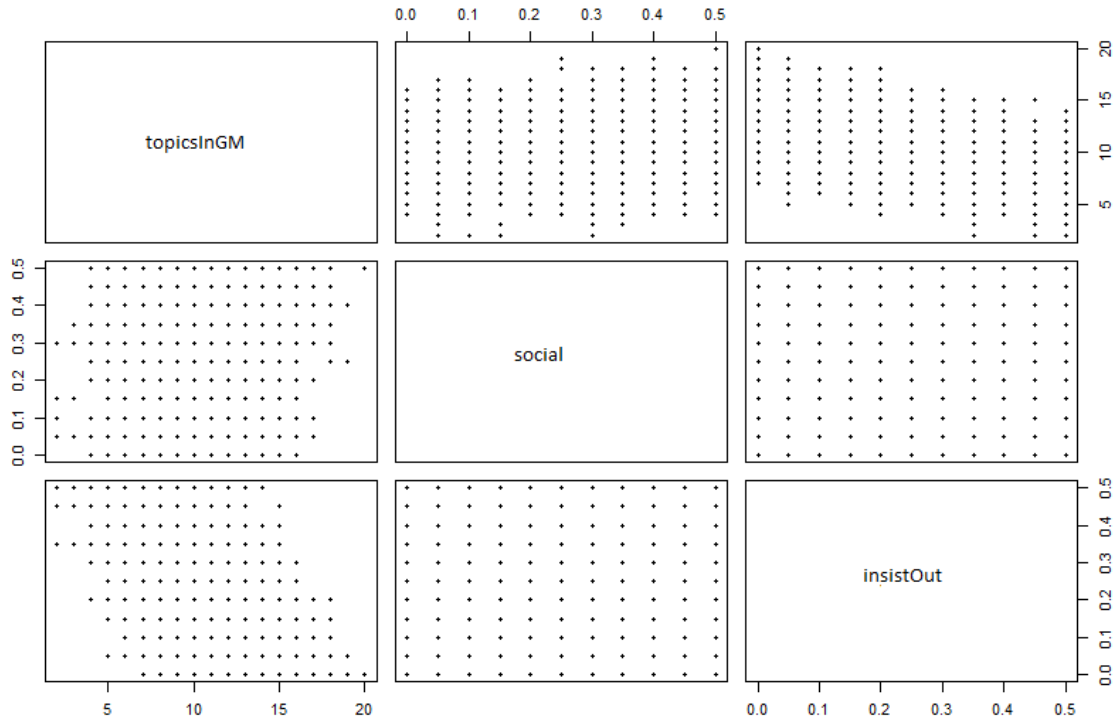
Fig. 9: Conformity fosters a broad consensus, while the influence of a controversy discussion is converse
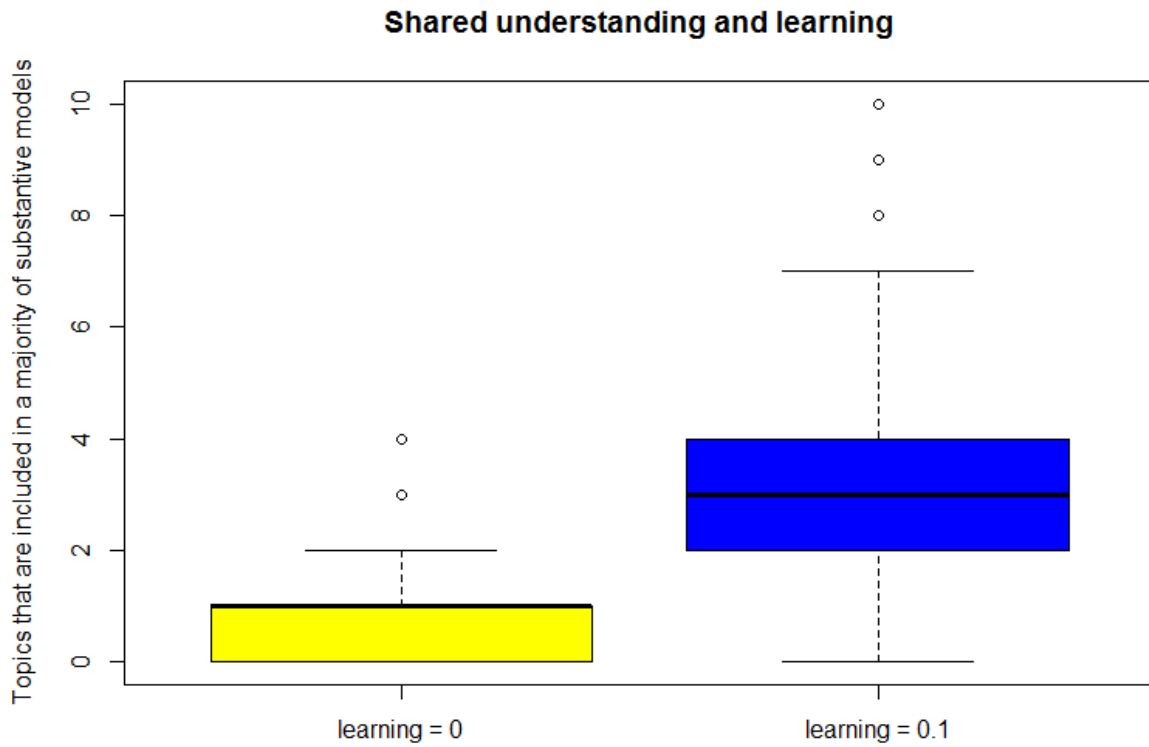
Fig. 10: Boxplot of the influence of learning on the building of a shared understanding
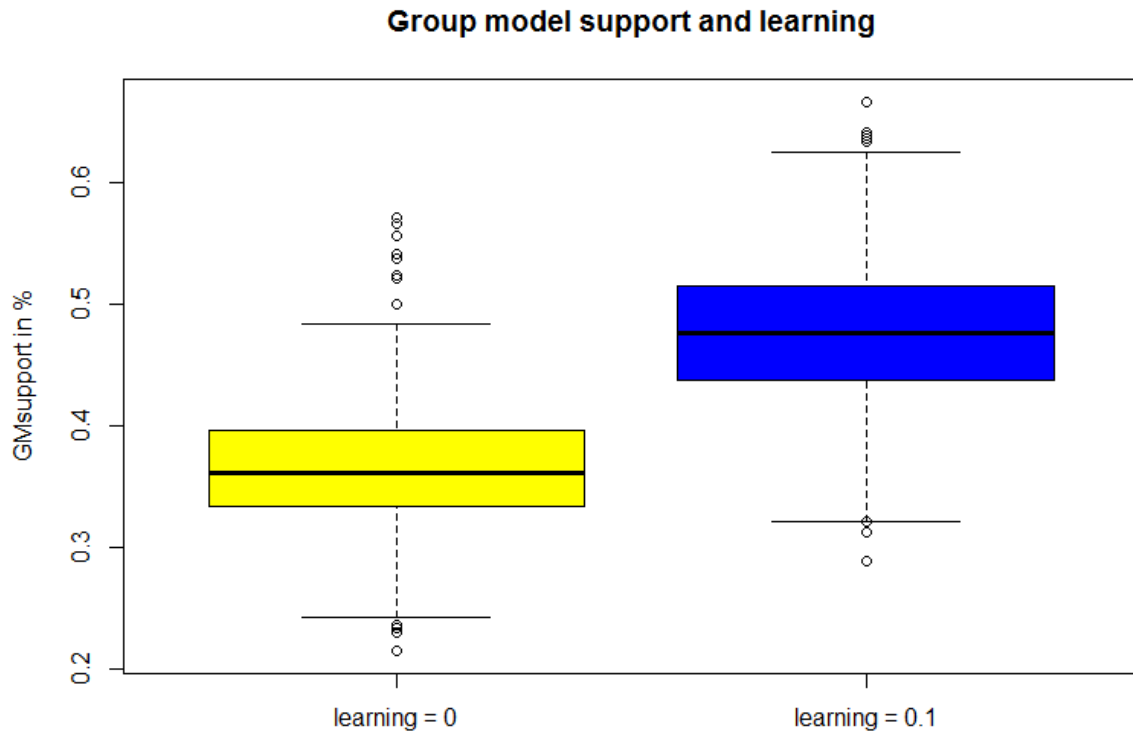
Fig. 11: Boxplot of the influence of learning on the support for the group model

The other main finding concerns relationships, i.e. mutual esteem. A high average role (which can be interpreted as the building of trust and positive relationships) correlates positive to substantive learning, the factual support for the group model, and to the building of a shared understanding. A high average role value at the beginning has a positive influence on the learning process. This can be interpreted as already existing relationships (high mutual esteem). Furthermore, the development of a higher average role during the process correlates positively to the building of a shared understanding. Thereby, the strong influence of *learning* on both of these indicators should be kept in mind. If learning takes place, a positive average role can be established during the process. Relational learning, referring to the changes in roles, is implemented in CollAct to be influenced by a similarity of opinions, which is similar to shared understanding. Hence, in CollAct a high average role (high mutual esteem) and high shared understanding influence each other in a positive way. The correlation between the average role, the shared understanding, and the support for the group model are depicted in Figure 12.
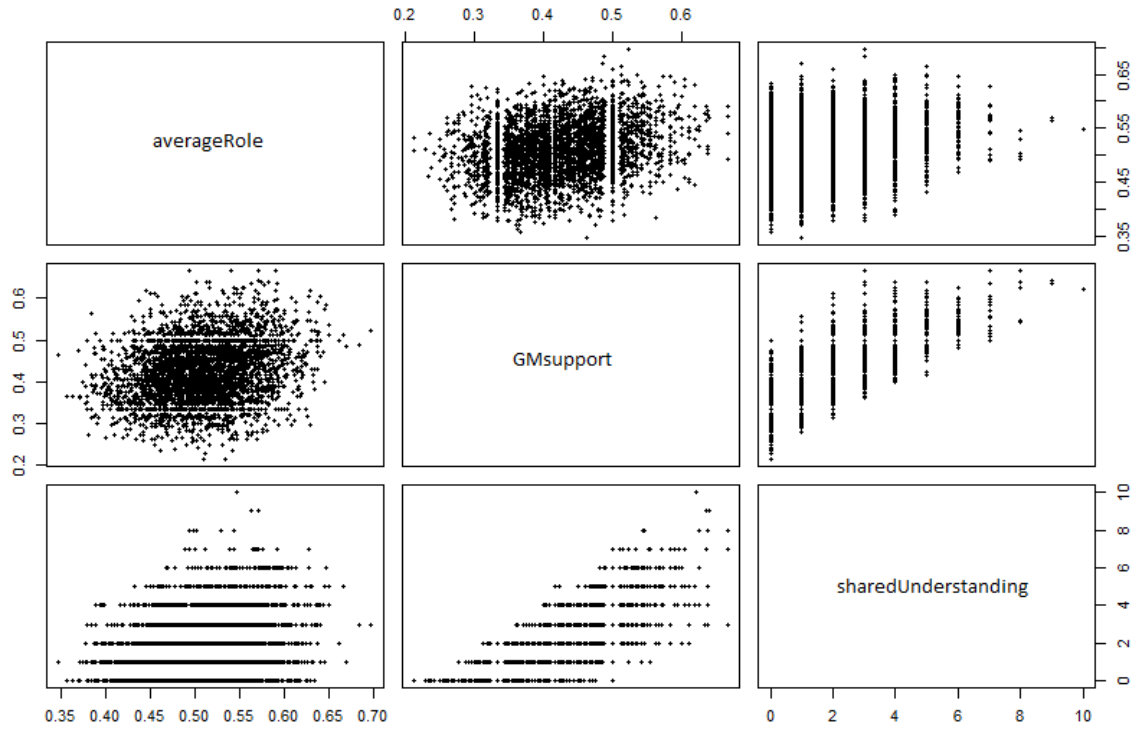
Fig. 12: A high average role and high shared understanding influence each other in a positive way

Discussion

A strength of CollAct is that it does not only model social contagion, but also includes individual learning, thus allowing the simulation of the building of a shared understanding. CollAct simulates discussions with successional clusters of messages on the same topic. Change of topics, the emergence of a consensus, the development of a shared understanding, and the shift and emergence of roles are also reproduced. Results that are confirmed through empirical findings include the sensitivity of the group size (Baron & Kerr 2003) and the observation that homogenous and smaller groups may speed up decision processes (Irvin & Stansbury 2004).

Factors identified as having an important influence on the topics included in the group model and the amount of substantive learning include the level of controversy within the discussion, cognitive diversity and available knowledge, and social behavior in form of cognitive biases (Asch and halo effect). This consistent with factors identified in the literature accounting for the fostering of social learning: open communication, unrestrained thinking, and multiple sources of knowledge (e.g., Muro & Jeffrey 2008). Another straight forward finding is that the integration of topics into the consensus follows a saturation curve.

The amount of conformity and controversy of the discussion are important parameters, which do not produce a straight forward finding of the kind 'the more the better', but relate to a trade-off between finding a consensus and allowing the building of a shared understanding and true support of the consensus reached. If a consensus is produced that is not truly supported by a majority, this can be interpreted as a form of problematic group dynamics (see Cooke 2001).

Another finding of CollAct is that a high average role (which can be interpreted as the building of trust and positive relationships) correlates positively to substantive learning, the factual support for the group model, and the building of a shared understanding. This influence is visible for a high average role at the start of a simulation run (which can be interpreted as existing high mutual esteem at the beginning), and the development of a high average role throughout the simulation. The latter can be interpreted as trust, commitment, and reframing as emergent and interrelated aspects occurring in the process of social learning as described by Sol et al. (2013).

Concluding remarks and outlook

CollAct models the interaction of participants in a discussion, including cognitive and relational learning as well as conformity and relational influences modeled through the use of cognitive biases. CollAct provides a starting point for determining group interaction during social learning processes. Thereby, CollAct proved useful for analyzing trade-offs in group interaction and as a thinking-tool. The understanding of face-to-face group interaction, including conformity and social decision schemes, is relevant for many current and crucial questions, such as policy decision making at all levels or even the work of juries (Baron & Kerr 2003).

While all of the results have to be considered with care because CollAct is a complex model embracing several uncertainties and simplifications, the findings underline the need for social learning to reach a consensus which is truly supported by a majority, and to gain support for solutions found. The importance of conformity and controversy for the established consensus, particularly in relation to the building of a shared understanding, are important factors which present interesting questions for future research.

It is important to further validate and explore CollAct by strengthening the link to empirical research and by including more socio-psychological findings. A next step we plan is linking the evaluation of case studies to CollAct. Interesting aspects can be simulated in the model, which can be run with the data of case studies. In this way, the results of CollAct can be compared to the evaluation of case studies, and further model validation and insights to the specific case studies are possible.
There are several questions for which an exploration with CollAct might be useful, as well as further explorations that could be used to strengthen results. The possible extensions of CollAct include:

- An exploration of the influence of different mental model combinations and the occurrence of new topics (ideas). This would allow for the modeling of inventions.
- An extension of CollAct, including diverse social learning entities in the form of group interaction settings which are linked in a network, could aid the analyses of the impact of learning on wider social units.
- A variation of underlying assumptions for learning and/or decision-taking together with an evaluation if results stay robust, respectively how results change, would aid the validity of CollAct and add to the discourse of learning and discussion models.
- The modeling of more detailed speech interaction influences: CollAct provides an interface that allows for the easy extension of CollAct with speech probabilities depending on more factors. This could offer further validation possibilities, and thus add to the validity of CollAct.

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8 CONCLUSIONS

In this thesis, I make an effort to better understand if and how participatory methods applied during participatory processes in natural resource management can serve as nuclei for social learning. In this section, I summarize the key findings.

The thesis is presented in a cumulative manner, comprising the current framing document (Chapters 1, 2, 3 and 8) and four research articles. The framework developed in Paper I (Chapter 4) can be used to analyze the results of participatory methods with respect to social learning, to explore if and when personal views of a problem converge into a shared understanding of a problem, and to assess how individual mental models and group properties relate. It can be applied for empirical research and facilitate comparative analyses. Suggested methods to measure social learning are supplemented by Paper II (Chapter 5), in which a method for comparing individual models with a group model is proposed. Furthermore, the framework offers a clearly defined description of integrated elements along with a structure for combining them. The framework is used to construct an agent-based model of group interaction within the setting of a discussion. This model, CollAct, considers both cognitive and relational knowledge and learning. CollAct is an explorative model built around the question of how people gain a shared understanding and reach a consensus[13] in an interactive group setting. Agents in CollAct discuss an abstract issue, trying to reach a consensus. To analyze the simulation output the indicators developed in the scope of the framework (Paper I) as well as the measures developed in Paper II are incorporated into output indicators. This procedure provides future possibilities for comparing model results with empirical data. Results of the model exploration are presented in Papers III and IV (Chapters 6 and 7).

This concluding chapter starts with a critical reflection on the research approach. I then address the aim of this thesis and draw conclusions by answering the research questions posed in Chapter 1. At the end, I provide an outlook on further research possibilities.

8.1 REFLECTION ON RESEARCH APPROACH

To answer the question of whether social learning occurred, it is necessary to discuss *what* exactly social learning is. The recent focus on cognitive learning and the former focus on the social-relational aspects of learning for the evaluation of social learning facilitated through participatory processes (see Section 2.2.3) illustrate the need for a common definition of social learning. In the absence of a commonly used conceptual framework it is difficult to position

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[13] I mean by consensus a general agreement. This might as well be a 'perceived general agreement', if participants of a discussion have doubts or disagreements but do not communicate them (for one reason or another).

empirical research results within the discourse, leading to a fragmentation of research (Rodela, 2013). A commonly used definition can help in the comparison of research results and gaining a better understanding of when social learning is especially useful and how it can be supported. However, there are voices which argue against one single definition of social learning. Ison et al. (2013) state that

> *"Rather than seeking to define social learning rigidly, and thus limiting its potential utility to open up spaces for innovation in sustainability and natural resource governance, social learning can be positioned in future discourse so that it holds a cluster of revealing and concealing features. Such a position then shifts responsibility for clarity and rigour away from the concept, useful because of its fluidity, to the user of the concept who must then articulate the way(s) in which they choose to use it."* (Ison et al., 2013, p. 40).

This may be linked to the ambiguity in the conceptualization of social learning discussed in Sections 2.1 and 2.2: On the one hand, social learning is employed as a facilitating framework for participatory planning, while on the other, participation is expected to facilitate social learning, being a (continuous) process with an outcome. To compare results of research on social learning, at least a standardized set of information included in descriptions of social learning would be valuable.

In this thesis, I investigate whether or not participatory methods applied in natural resource management facilitate social learning, and how this can be achieved. For this endeavor I chose and extended the definition proposed in Reed et al. (2010). Even if this definition focuses on certain aspects of social learning metaphors and inevitably leaves out other aspects, it allows for the comparing and positioning of research results. Furthermore, it allows for the comparison and discussion which types of learning are likely to occur under what circumstances (e.g., convergent or divergent learning), and thus helps to set the conditions and incentives likely to result in desired outcomes.

I combined the chosen definition with an analytical framework of social learning facilitated by participatory methods (see Paper I). This framework concentrates on the learning processes at the individual and group level facilitated within a participatory method. In the context of participatory methods it is difficult to analyze the diffusion of ideas and attitudes of participants to their wider social units or communities of practice. Although this issue is important in social learning theories, it could not be addressed within the scope of this thesis, and is thus left to further research.

A delicate issue is the measurement of mental models. Mental models are a core component of the framework developed in Paper I, the methods proposed in Paper II, and for CollAct. Because mental models exist within the minds of individuals, they cannot be analyzed directly (see also Papers I and II). Moreover, they can change during elicitation (Doyle & Ford, 1999). While different techniques exist for the elicitation of mental models, the appropriate elicitation techniques still remain a challenge for further research (Jones et al., 2011). It is important to keep

in mind that the use of any tool affects what is measured (Lynam et al., 2012). Externalized mental models are influenced by the internal mental model, the elicitation method employed, and the mental model of the facilitator/modeler (Kim, 2009). If mental models change during elicitation, this questions the objectivity and reproducibility of research results. The difficulty of observing mental models does not apply to agent-based models. Accordingly, an advantage of simulating group interaction is the possibility of observing mental models as represented within agents throughout the simulation.

Lastly, CollAct incorporates a number of uncertainties which should be kept in mind. Participants are modeled in a rather complex, cognitive fashion. Accordingly, a number of design choices were necessary with respect to assumptions and parameters. Wherever possible, design choices were based on empirical results or theory. Empirical evidence was not sufficient to estimate the parameters for learning (Brenner, 2006). However, for the explorative aim of CollAct, conducting parameter sweeps was sufficient for estimating the influence of parameter changes. Nevertheless, further testing and backing results up with empirical finding would significantly strengthen the conclusions. This was beyond the scope of this thesis and presents the need for further research. Hence, model results and the following propositions should be seen as ideas which can guide further research and be supplemented by empirical evidence.

8.2 ANSWERING THE RESEARCH QUESTIONS

To present the main insights of this work, I respond in this section to the research questions posed in Chapter 1.

8.2.1 RQ1: (How) does social learning occur during the use of participatory methods within resource management?

What can be said of the current state of research: do participatory processes facilitate social learning?

Empirical findings suggest that participatory processes may enhance social learning. Until very recently empirical evidence for the claim that participatory processes foster social learning was rare, and mainly social-relational outcomes were reported, partly due to the absence of a common definition and missing methods to quantify social learning (see Sections 2.1 and 2.2). In the last five years some efforts were reported that also measured the cognitive aspects of social learning (Haug et al., 2011; Mathevet et al., 2011; Raadgever, 2009; van der Wal et al., 2014). Thereby changes in externalized mental models and perspectives of stakeholders were quantified and evaluated. Most of these studies conclude that learning occurred. Additionally, the intensity of the collaboration appears to be an important factor for the amount of learning. However, the recent studies use different methods to measure whether or not learning occurred and

evaluate different settings[14]. Furthermore, most of them focus on cognitive learning[15]. Thus, further research in this area is needed to compare data and to include relational aspects, which are an important element of most social learning theories.

<u>Which definition serves best to operationalize social learning?</u>

A commonly agreed upon definition for social learning as well as a shared understanding of the processes entailed is still missing (Muro & Jeffrey, 2008; Reed et al., 2010; Rodela, 2013). I identified the definition in Reed et al. (2010) to best serve the purpose of this thesis (see Section 2.1.2), providing a basis for formalization. Accordingly,

> *"[T]o be considered 'social learning,' a process must:*
> *(1) demonstrate that a change in understanding has taken place in the individuals in-volved;*
> *(2) demonstrate that this change goes beyond the individual and becomes situated within wider social units or communities of practice; and*
> *(3) occur through social interactions and processes between actors within a social net-work".*(Reed et al., 2010, p.1)

Nevertheless, this definition does not take into account whether or not stakeholders learning together reach a shared understanding. This is important, because there might be some learning taking place, while positions harden on both sides and the common ground decreases. To ad-dress this issue I suggest adding the direction of learning, being either convergent or divergent (see Paper I). Convergent learning refers to an increase in shared understanding, and means that actors integrated new perspectives gleaned from each other, and/or developed new shared con-cepts. Recent empirical research supports the need of a distinction between divergent and con-vergent learning (Vinke-de Kruijf et al., 2014; van Mierlo, 2012).

<u>Which indicators are suitable for measuring and monitoring social learning?</u>

The various definitions result in the selection of different indicators to report if social learning took place during participatory processes. This hampers the comparability of findings. I suggest a set of indicators to evaluate whether or not social learning took place, referring to the above definition (see Paper I):

1. Change in mental models (substantive and relational);

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[14] The settings evaluated varied between a policy exercise (Haug et al., 2011), participatory processes in water and land management (Raadgever, 2009; van der Wal et al., 2014), and learning in a Water Board (Mathevet et al., 2011).

[15] Haug et al. (2011) also report on relational and normative learning.

2. Impact of substantive and relational outcomes in the wider context; and
3. Increased similarity between mental models.

These indicators denote cognitive and relational learning.

<u>Are there methods to measure these indicators? If not, how could the suggested indicators be measured?</u>

The framework I developed in Paper I concentrates on the learning processes at the individual and group level facilitated within a participatory method (see above). It is therefore difficult to analyze the impact of substantive and relational outcomes in a broader context. The key questions for analyzing such an impact are (i) whether the substantive outcomes of the participatory method are built upon in a wider community (e.g., in policy development), and (ii) whether the relational outcomes of the participatory activity have a broad impact in the wider community (e.g., increased trust between actors). As stated above, the focus here is on participatory methods, leaving influences in broader social units for further research.

Various approaches exist for measuring mental models. The recent approaches, which compare mental models or perspectives, all use different methods[16]. In Paper I, I propose the use of concept maps for the measurement of externalized mental models. Although the elicitation of mental models is a delicate issue (see above discussion), concept maps are expected to represent something very similar to cognitive reasoning (Mohammed et al., 2000). Furthermore, concept mapping has already been applied in resource management (Kolkman, 2005; Pahl-Wostl & Hare, 2004) and for the evaluation of learning in various contexts (e.g., Haug et al., 2011; Mohammed et al., 2000; Morine-Dershimer, 1993). To analyze change in concept maps I discuss methods in Paper I while proposing a categorization and comparison of included concepts and relations. This approach can shed light on learning, and on the development of a shared understanding (denoted by an increased overlap of mental models). To measure relational learning, I propose an analyses of the effects of the participatory method on roles. This includes a number of dimensions: feelings of involvement, urgency and responsibility, the belief in one's own skills and freedom of maneuver, perceived feelings of dependence, and trust in efforts, skills and capacities of other group members (van Mierlo et al., 2010). Roles can be measured through observation and/or interviews and questionnaires.

Suggested methods to measure social learning are supplemented by Paper II (Chapter 5), because no methods for the comparison of individual mental models with a group model could be found. The group model developed during a group model building exercise offers further opportunities for analyses by revealing which actor brings topics from his or her personal model

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[16] Methods used are the Q-methodology (Raadgever, 2009), cultural consensus analysis (Mathevet et al., 2011), measures used in educational research (Haug et al., 2011), and cultural theory (van der Wal et al., 2014).

to the group model. This comparison can be used to estimate how much influence an actor exerted, and then compared to the analysis of roles. I addressed this research gap in Paper II by proposing matrices and Venn diagrams to visually compare concept models and a group model. Furthermore, Paper II proposes and tests methods to evaluate: (i) if all participants were able to include their point of view (this can be complemented by a questionnaire), (ii) how the facilitator performed in managing the dominance of participants, and (iii) if new concepts which no participant mentioned before emerged out of the process. Categories that appeared only in the group model and not in a concept map indicate that learning took place during the group model building process.

Which elements and processes on the individual and group level are important for social learning?

The analytical framework developed in Paper I of this thesis displays elements and processes important for social learning at the individual and group level. The framework builds upon the Management and Transition Framework (MTF), which was developed to allow more precise analyses of water management processes (Pahl-Wostl et al., 2010). Starting from this, I extend the mental model concept to be a core component. I conceptualize mental models to contain two sub-models: the substantive model, which includes knowledge about the topic at hand, and the relational model, including knowledge about other actors (e.g., personal characteristics) and self-perception. Furthermore roles taken up in the process by actors are deemed important, and may shift or emerge during the process through engagement or through attribution by other participants. The emergence or shift of roles at the group level is based on changes in the relational models of actors. Actors' relationships and the creation of trust can be captured in the concept 'relational outcome'. Further elements of the framework include a structured interaction context (the action situation), actors, shared understanding, and substantive outcomes (see Paper I).

Mental models proved to be especially useful for bridging the dichotomy of individual actors and the group by linking relational models (as belonging to an actor) to roles at the group level. Furthermore, mental models determine the interpretation of information from the environment (see Section 2.4.2 and Paper I). Thus, the division of mental models in relational and substantive models allows for the modeling of cognitive biases (see Section 2.4.3) and relational influences. Last, mental models are useful for analyzing the direction of learning, being either convergent or divergent.

Which processes and factors account for the fostering or hampering of social learning during the use of participatory methods?

Both context and process factors are important for the results of participatory methods and possible learning. Muro and Jeffrey (2008) summarize the following process features for fostering

social learning: facilitation, small group work, egalitarian atmosphere, repeated meetings/opportunities for interaction, opportunities to influence the process, open communication, diverse participation, unrestrained thinking, and multiple sources of knowledge.

Because of the focus of this thesis' on the application of participatory methods to facilitate social learning, process factors including social processes are of specific interest. Through group interaction, undesired dynamics may occur (Cooke, 2001). Another sensitive issue that may have negative impacts on group processes and the outcomes of participatory methods are power relations (Kothari, 2001). Considering the pitfalls which may arise in group dynamics, facilitation seems even more important. Dynamics occurring during group interaction are modeled within CollAct as part of this thesis to gain a better understanding of the interplay of different processes.

8.2.2 RQ2: How can social learning processes facilitated through participatory methods be reproduced in an agent-based model to gain a deeper understanding of involved processes and feedback?

<u>What are reasonable system boundaries for such a model?</u>

Process factors are important for social learning facilitated through the application of participatory methods, and group dynamics and power relations are delicate (RQ1). To be able to explore these influences in detail, I focus on a single event (a participatory event structured through a participatory method), and include relational aspects and the interaction process in the form of speech. Thus, I leave the question of whether learning took place in wider social units or communities of practice for future research. To construct an agent-based model, the focus is set on a main research question. CollAct is structured around the question of how a group of participants reaches a consensus and eventually develops a shared understanding of a topic at stake. While I used this question to focus model development, CollAct is meant to be an explorative model, allowing the analysis of diverse influences of individual characteristics (knowledge, roles), learning, social behavior, and group dynamics.

Some confinements were necessary to facilitate implementation and evaluation. First, speech occurs in a turn-taking manner, and all messages are heard by all participants. Second, I leave out the facilitator (in the first – current model version). Although facilitation is of key importance, simulating a group discussion without an active facilitator allows for the exploration of group dynamics and relational influences without the additional complexity of a 'managing role'. Finally, CollAct focuses on social processes and learning, taking conformity and relational influences into account. Emotions, such as anger, are not considered. Furthermore, influences of the social context (e.g., appropriate behavior, interaction rules) are not modeled explicitly. Instead, speech processes and cognitive biases are included. Because CollAct does not

include the wider social context nor facilitation, it is a model of learning and group interaction in discussions, and thus the results are not limited to the context of participatory methods.

<u>Which model structure and which concepts (elements, interactions, learning processes) are appropriate for modeling social learning processes facilitated through participatory methods?</u>

To appropriately model social learning facilitated through the application of participatory methods, group dynamics and power relations, as well as processes identified to be important for group interaction (e.g., conformity), should be considered. Thus, the model structure builds upon the theoretical considerations discussed in RQ1. The basis for the model structure is the developed framework (see Paper I). The mental models of participants, including a substantive and a relational model (see RQ1), are a core component. The knowledge of both mental model parts is used to interpret incoming messages and to decide upon learning (which may occur in both mental model parts) and possible options for actions (messages). Hence, the mental models of participants influence how information from the environment is interpreted, and therefore the interaction with the environment. Whether or not a participant tries to send a new message is determined by his/her role, and depends upon his/her perceived position within the group. This means that if a participant perceives himself/herself to be at a high (low) rank compared with other participants, the probability for speech increases (decreases). The information for this evaluation is saved within the relational model of participants. This leaves space for the emergence and shift of roles, because if learning in the relational models takes place this can have an impact on the distribution of speech participation among participants. The contents of messages with respect to the topic at stake are influenced by the substantive model of participants, but also by the perceived 'social' situation. To model these influences I use two cognitive biases: the Asch effect (Asch, 1951) and the halo effect (Thorndike, 1920). With the use of these theories, CollAct implements knowledge and biases at the individual level which produce a social situation that influences the further simulation. Other processes, for example learning, are modelled based on research results about mental models and learning, identified in the literature (see Section 2.4.3). Furthermore, a protocol is used to assure path-dependency in the discussion. Thus, various theories and concepts have been integrated in CollAct, to allow for a comprehensive model of group interaction during participatory methods.

<u>Is it possible to generate group phenomena?</u>

CollAct simulates discussions with successional clusters of messages on the same topic. Furthermore, a change of topic, different levels of controversy, learning, consensus, a shared understanding, and the shift and emergence of roles are reproduced.
CollAct produces several results that are confirmed through empirical findings. The group size is a highly sensitive parameter. The significance of group size is known to have a strong influence in empirical research (Baron & Kerr, 2003). The statement that homogenous and smaller groups may speed up decision processes (Irvin & Stansbury, 2004) is also supported through correlations produced by CollAct. Furthermore, factors that foster social learning, such as open

communication, unrestrained thinking, and multiple sources of knowledge (see RQ1), also have an important influence in CollAct: The inclusion of diverse knowledge fosters learning among participants. The amount of conformity and controversy taking place in the discussion are important parameters which do not produce a simple straight forward finding of the kind 'the more the better', but also relate to a trade-off between finding a consensus (here understood as a resulting group model) and allowing the building of a shared understanding and true support of the consensus achieved (see RQ3). If a consensus in the form of the group model is produced that is not truly supported by the majority, this can be interpreted as a form of group dynamic related to group think or Abilene paradox (see Section 2.2.4).

Another factor accounting for the fostering of social learning, the building of high mutual esteem is also reproduced in CollAct: A high average role (which can be interpreted as building of trust and positive relationships) correlates positive to substantive learning, the factual support for the group model, and the building of a shared understanding. This influence is visible for a high average role at the start of a simulation run (which can be interpreted as already existing high mutual esteem), and the development of a high average role throughout the simulation, which can be interpreted as the correspondent to trust, commitment and reframing as emergent and interrelated aspects occurring in the process of social learning as described by Sol et al. (2013).

While this is a promising start, results have to be considered with care, because CollAct is still a complex model embracing several uncertainties and simplifications.

8.2.3 RQ3: Is it possible to identify factors or processes that hamper/ foster social learning in participatory methods through model exploration?

What can be learned from model exploration?

The integration of substantive knowledge and relational knowledge and their interaction within the agent rules produce interesting dynamics, but also a large amount of data which has to be interpreted in a meaningful way. A straight forward finding is that the integration of topics into the group model follows a saturation curve. Hence, the time that discussions end should be carefully chosen to avoid a loss of information while optimizing time effort. Factors identified to have an important influence on the width of the consensus and on the amount of learning include:

- Group size;
- Controversy within the discussion;
- Cognitive diversity and available knowledge;
- A leading role at the outset (this influence depends on the group size); and
- Conformity in form of cognitive biases (Asch and halo effect).

Controversy and conformity are linked, because in fact a low level of controversy could stem from conformity. However, in CollAct both influences are modeled independently, allowing for a more detailed analysis.

A strength of CollAct is that it does not only model social contagion, but also includes individual learning to simulate the building of a shared understanding. It therefore allows for an exploration of the relationship between the reaching of a consensus and the development of a shared understanding. Two main conclusions of this exploration are:

1) High mutual esteem and the building of a shared understanding reinforce each other; and
2) Cognitive learning is needed to build a shared understanding and to increase the support of a possible consensus.

With respect to (1), a high average role (which can be interpreted as building of trust and positive relationships) correlates positive to substantive learning, the factual support for the group model, and to the building of a shared understanding. A high average role value from the beginning has a positive influence on the learning process. This can be interpreted as already existing relationships and/or positive experiences from prior joint participatory exercises. Furthermore, the development of a higher average role during the process correlates positive to the building of a shared understanding. Learning has a strong influence on both of these indicators.

With respect to (2), while high conformity and low controversy both foster a broad consensus, this does not lead to a higher shared understanding among participants, and also does not lead to a strong support of the consensus (overlap with mental models of participants). On the other hand, learning has a strong positive influence on the support of the consensus and on the shared understanding among participants. Thus, in CollAct substantive (cognitive) learning is needed to build a shared understanding, while conformity and relational influences are sufficient to agree upon a 'consensus' that is not truly supported by a majority of participants.

These findings further underline the importance of considering both relational and cognitive knowledge and learning when analyzing social learning and group interaction.

<u>Which questions or possible suggestions can be attributed to empirical research and participatory practice?</u>

The simulation of processes on the cognitive individual level lead to reasonable outcomes at group level, and allow the exploring of issues discussed in current research on the facilitation of social learning in participatory processes. By including a substantive and a relational model, individual characteristics, influences and interpretations on the factual level and influences and

interpretations on the relational level are grasped. The dynamics produced through their inter-ference suggest that the division in cognitive and relational knowledge used to evaluate social learning (see Section 2.1.3) appears to be artificial. Both kinds of knowledge should be considered when evaluating social learning results of a group process. While doing this, the sensitive issue of power relations can be grasped as well. The level of controversy and conformity are important factors influencing the results in CollAct. These results strengthen the importance of facilitation of group processes. While the level of controversy and conformity both have an important influence, this influence is not of the kind 'the more the better'- rather controversy and conformity should be balanced in a cautious way, presenting a challenge for facilitation.

Furthermore, results suggest that substantive (cognitive) learning is needed to build a shared understanding, while conformity and relational influences are sufficient to agree upon a 'consensus' that is not truly supported by a majority of participants. Thus, to exploit the expected benefits from participation to foster the building of a shared understanding, and to foster the durability of achieved decisions through greater support of the public (effectivity claim), it is important to engage in cognitive learning. The extent to which people learn depends on a number of factors. Raadgever (2009) concludes that only intense collaboration enhance learning, including many meetings, intense discussion of perspectives, and an active participation in the research. Furthermore, other actors influence learning, such as participants' willingness and also their ability to learn and to cooperate (Raadgever, 2009).

Another result of CollAct is that high mutual esteem and the building of a shared understanding reinforce each other. A high average role value from the beginning has a positive influence on the learning process. By influencing learning in a positive way, this may again influence the average role in a positive way, and therefore a reinforcing process can 'spin up' social learning. Sol et al. (2013) describe trust, commitment and reframing as emergent and interrelated aspects, that occur in the process of social learning and influence each other as well as the further process. CollAct can serve as a thinking-tool to explore such ideas. Looking at the practice, the building and maintaining of high mutual esteem in form of good relationships may serve as an enforcing factor for social learning. Hence, investing in a good atmosphere and leaving space for relational learning may result in net benefits even in terms of cognitive learning in the long run.

In summary, results of CollAct suggest that in order to exploit the benefits claimed of social learning and participation, both cognitive and relational learning should be facilitated. This endeavor is time consuming. Therefore, the decision of whether or not social learning should be a main goal of a participatory process in question should be carefully considered[17]. However, CollAct's findings underscore the need for social learning to find an agreement which is truly

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[17] For suggestions on how to take such a decision see Irvin & Stansbury (2004).

supported by participants and thus exploit the promise that participatory methods hold to facilitate the generation of solutions to gridlocked (messy) problems, and to gain wide support for the solutions identified.

8.3 IMPLICATIONS FOR FURTHER RESEARCH

During this work, further research questions and interesting considerations arose, which could not be answered within the scope of this thesis. These suggest areas for further consideration or research, and are summarized in this final section.

To foster and implement change, social learning processes initiated at local level need to be accompanied by change at higher institutional levels (Pahl-Wostl et al., 2013). Given that the focus of this thesis was on group interaction during the application of participatory methods it was not possible to analyze the diffusion of ideas and attitudes learned by participants to their wider social units or communities of practice. The question how social learning processes and resulting ideas get diffused to wider social units is highly significant for fostering and achieving desired changes in natural resources management and in the wider discourse on sustainability. Hence, it would be interesting and meaningful to link the results of this thesis to approaches that address broader social units, such as network analyses. A network analysis can provide a complementary understanding of learning processes especially at group and network level through formal quantitative analyses (see, e.g., Bodin & Crona, 2009; Methner, forthcoming; Newig et al., 2010).

The framework developed in Paper I offers the possibility to link the analyses of social learning facilitated through participatory methods to wider social units, while supporting an analyses of the direction of learning. When looking at the influences of social learning in the wider social context, the direction of learning (being convergent or divergent) is important as well. Divergent learning may spread new ideas and increase the number of possible options, while convergent learning is linked to social learning as defined within this thesis, allowing for the building of a shared understanding that may lead to collective action and change. In terms of research into transitions, this is discussed by van Mierlo (2012), who finds that both types of learning may coexist and can be useful for different purposes concerning niche development.

A next step is the testing within empirical research. The framework developed in Paper I is tailored to the application in empirical research and particularly suited for comparative case study analyses. The same applies to the method developed in Paper II, which can be used to complete analyses conducted with the help of the framework, or as a stand-alone method to evaluate group model building processes. I suggest group model building as a first area of application for the framework, because then the method presented in Paper II could be integrated and the full analytical potential of the framework could be exploited. Linking the evaluation of

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case studies to CollAct is of interest as well. CollAct is a useful tool for exploring the interdependence of variables affecting learning and consensus finding during the application of participatory methods. Aspects of interest for further investigation can be simulated in the model, which can be run with case study data. In this way, results of CollAct can be compared to the evaluation of case studies, and further model validation and insights to the specific case studies are possible.

CollAct proved to be useful for analyzing trade-offs in group interaction and as a thinking-tool. The understanding of face-to-face group interaction, including conformity and social decision schemes, is relevant for many current and crucial questions, such as policy decision-making at all levels or even the work of juries (Baron & Kerr, 2003). There are many more questions for which an exploration with CollAct might be useful, as well as further explorations that could be used to strengthen results. Possible extensions of CollAct include:

- An exploration of the influence of different mental model combinations and the occurrence of new topics (ideas). This would, for example, allow for the modeling of innovations, and convergent and divergent learning.
- An extension of CollAct, including diverse social learning entities in the form of group interaction settings which are linked in a network, could aid the analyses of the impact of convergent and divergent learning on wider social units.
- A variation of underlying assumptions for learning and/or decision-taking together with an evaluation of the robustness of results, respectively how results change, would aid to the validity of CollAct and add to the discourse of learning and discussion models.
- The modeling of more detailed speech interaction influences: CollAct provides an interface that easily allows for the extension of CollAct with a variety of factors determining speech participation of participants. This could offer further validation possibilities, and thus add to the validity of CollAct.

Finally, the results of this thesis, particularly the agent-based model, do not only apply to the area of natural resource management and the application of participatory methods. The model CollAct might also serve to model group discussions, consensus building and/or learning in other domains.

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APPENDIX

This appendix includes the source code of CollAct. A running version of CollAct can be found in the CoMSES Net Computational Model Library (https://www.openabm.org/model/4255/version/1/view)[18].

Classes are displayed in the following order:

1. Discussion

2. Facilitator

3. Message

4. Model

5. Participant

6. Protocol

7. Role

8. SessionBuilder

1. Discussion

package collAct;

import java.util.LinkedList;
import repast.simphony.engine.schedule.ScheduledMethod;
import repast.simphony.engine.environment.RunEnvironment;

```
/**
 * @author Geeske Scholz
 * This class provides a room for discussion, representing the air or virtual room.
 * All Participants and the Facilitator know their discussion, and are able to call up
 * discussion.getLast() to "hear" the last spoken message. Because CollAct models a turn
 * taking conversation, only one of the registered messages per round is chosen (by discussion).
 * Which message is chosen is decided randomly, using the implementation
 * of Repast, which calls up step of the agents in a randomized way.
 * Furthermore this class provides end routines for model evaluation.
 */
public class Discussion {
        LinkedList<Message> messages;
        Protocol protocol;
        int c;                          /* speaker of last spoken message (-1 if nobody speaks) */
        int t;                          /* topic of last spoken message (-1 if nobody speaks) */
        Message last;                   /* last message */
        int participants;              /* how many agents participate in this discussion */
        int [] speechDistribution;      /* saves number of speech acts for each agent */
        int silenceStop = 20;           /* after this number of steps without a speech CollAct is stopped */
        int silenceCounter;             /* counter for subsequent time steps with silence */
        double [] roles;                /* sum of roleMappings/participants (roles[i] has the sum value of
                                           all roleMapping[i]s/number of participants) */

        /**
         * Constructor
         * @param pParticipants
         */
        public Discussion(int pParticipants) {
                c = -1;                 /* speaker default/error value */
                t = -1;                 /* topic default/error value */
                protocol = new Protocol ();
                messages = new LinkedList<Message>();
                last = null;            /* last message */
                participants = pParticipants;
                speechDistribution = new int [participants];
                silenceCounter = 0;
                roles = new double [participants];
        }

        /**
         * When this method is called up a new Message is memorized for the current round
         * (added to the list).
         * @param m
         */
        public void speak(Message m){
                messages.add(m);
        }

        /**
```

```
 * The current last Message is returned (last speech act).
 * @return Message
 */
public Message getLast(){
        if (last != null){
                return last;
        }
        else {
                return new Message (-1,-1,true); /* default values */
        }
}

/**
 * Provides the most likely topic concerning the protocol.
 * @return topic (int)
 */
public int mostLikelyTopic(){
        return protocol.mostLikelyTopic();
}

/**
 * Step is called up every round. Thereby it is checked which messages have been sent and the
 * last message is chosen to be the current message and entered in the protocol.
 * All data fields are updated. If silenceCounter is greater than
 * silenceStop the simulation is ended.
 */
@ScheduledMethod(start = 1.5, interval = 1.0)
public void step(){
        /* default values for no speech acts */
        c = -1;
        t = -1;

        /* last message is seen, though a random distribution of speakers is realized */
        if (messages.size() > 0){
                last = (Message) messages.getLast();
                protocol.add(last);
                c = last.getSpeaker();
                t = last.getTopic();

                if (c >= 0){
                        speechDistribution [c]++;
                }
        }

        /* update silenceCounter */
        if (c == -1){
                silenceCounter++;
        }
        else {
                silenceCounter = 0;
        }

        /* messages from last round are deleted */
        messages.clear();

        if (silenceCounter > silenceStop){
                /* simulation (discussion) may be ended because nobody speaks */
```

```
                    RunEnvironment.getInstance().endRun();
            }
    }

    /**
     * Calculates how many of all participants wanted the current topic to be included (at least
     * as far as it is saved in the protocol- following this it also depends on the forget)
     * @return share of participants that wanted to include a topic (double)
     */
    public double topicShare (){
            return (double) protocol.topicCount(t) / participants;
    }

    /**
     * Method to update the representation of role sums/participants at the beginning
     * @param role
     */
    public void setRole (Role role){
            for (int i = 0; i < participants; i++) {
                    double temp = (role.person(i)) / participants;
    roles[i] += temp;
}
    }

    /**
     * Method to update the representation of role sums/participants for single entries
     * @param x (number of the participant to be changed)
     * @param y (change)
     */
    public void setRole (int x, double y){
            roles[x] += (y / participants);
    }

    /* The following part consists of methods which produce data for charts and evaluation */

    /**
     * Produces data for a chart to show who's speaking. -1 if nobody is speaking.
     * @return who is speaking (int)
     */
    public int whoIsSpeaking(){
            return c;
    }

    /**
    * Produces data for a chart which displays how many messages treat a certain topic. -1 if no speech act *
    occurred.
     * @return topic (int)
     */
    public int topic(){
            return t;
    }

    /**
     * Calculates range of roles. Data for evaluation.
     * @return distance of lowest to highest role
     */
    public double rangeOfRoles () {
```

```
        double lowest = 0;
        double highest = 0;
        boolean start = true;

        for (int i = 0; i < participants; i++){
                if (start){
                        lowest = roles[i];
                        highest = roles[i];
                        start = false;
                }
                else {
                        if (lowest > roles [i]){
                                lowest = roles [i];
                        }
                        if (highest < roles [i]){
                                highest = roles [i];
                        }
                }
        }

        /* calculate and return distance */
        return highest - lowest;
}

/**
 * Calculates the average role. Data for evaluation.
 * @return average role
 */
public double averageRole () {
        double average = 0;

        /* sum up roles */
        for (int i = 0; i < participants; i++){
                average += roles[i];
        }

        /* calculate and return average role */
        if (participants > 0){
                return average / participants;
        }
        else {
                return average;
        }
}

/**
 * Calculates the distance of the highest role to the next role. Data for evaluation.
 * @return distance of the highest role to the next role
 */
public double leadingRole () {
        double next = 0;
        double highest = 0;
        boolean start = true;

        for (int i = 0; i < participants; i++){
                if (start){
                        next = roles[i];
```

```java
                    highest = roles[i];
                    start = false;
                }
                else if (highest < roles[i]) {
                    next = highest;
                    highest = roles [i];
                }
        }

        /* in case that the first role (0) was the highest,
         * the next part finds the next highest role */
        if (highest == next){
                if(participants > 1){
                    next = roles[1];
                }

                for (int i = 2; i < participants; i++){
                    if (next < roles[i]) {
                        next = roles [i];
                    }
                }
        }

        /* calculate distance */
        return highest - next;
}

/**
 * Calculates range of speech acts per Participants in %. Data for evaluation.
 * @return range of speech acts in %
 */
public double rangeOfSpeechParticipation () {
        double lowest = 0;
        double highest = 0;
        int speechActs = 0;
        boolean start = true;

        for (int i = 0; i < participants; i++){
                if (start){
                    lowest = speechDistribution[i];
                    highest = speechDistribution[i];
                    speechActs = speechDistribution[i];
                    start = false;
                }
                else {
                    speechActs += speechDistribution[i];
                    if (lowest > speechDistribution [i]){
                        lowest = speechDistribution [i];
                    }
                    if (highest < speechDistribution[i]){
                        highest = speechDistribution [i];
                    }
                }
        }

        /* calculate range of speech acts in % */
        double range = highest-lowest;
```

```java
		if (speechActs > 0){
				return (range * 100 / speechActs);
		}
		else {
				return -1; /* error value; no speechAct occurred */
		}
	}
}
```

2. Facilitator

```java
package collAct;

import java.util.Iterator;
import repast.simphony.context.Context;
import repast.simphony.engine.schedule.ScheduledMethod;
import repast.simphony.util.ContextUtils;
import repast.simphony.util.collections.IndexedIterable;

/**
 * @author Geeske Scholz
 * Facilitator holds the group model, which is the result of the discussion.
 * Furthermore it offers methods for the graphical display in Repast and
 * end routines for evaluation.
 */
@SuppressWarnings("unused")
public class Facilitator {

	int size;				/* number of possibly included topics */
	int [] consent;			/* used to evaluate the consent on a topic and decide on integration
							 in the group model */

	int consentLevel;		/* consent level needed to integrate a topic in the group model */
	int [] possibleTopics;	/* array which includes all topics participants know about, and how
							 many participants know about a certain topic */

	Model groupModel;
	Discussion discussion;

	/**
	 * Constructor
	 * @param pDiscussion
	 * @param pSize (number of possibly included topics)
	 * @param pHowMany participants take part in the discussion
	 * @param pPossibleTopics (model which includes all topics participants know about)
	 */
	public Facilitator (Discussion pDiscussion, int pSize, int pHowMany, int [] pPossibleTopics){
		discussion = pDiscussion;
		size = pSize;
		consent = new int [size];
		groupModel = new Model(size);
		consentLevel = pHowMany; /* the consent level necessary to include a topic in the group
									model is set to the number of participants */
		possibleTopics = pPossibleTopics;
	}
```

```
/**
 * Step is called up every cycle. The last message is evaluated and eventually changes in
 * consent are realized.
 * Depending on consent new topics can be integrated in the group model, and topics
 * already agreed upon may me taken out again.
 */
@ScheduledMethod(start = 1.1, interval = 1.0)
public void step(){
        Message last = discussion.getLast();
        int current = last.getTopic();

        if (last.getIn() && (current != -1)){
                consent [current]++;
        }
        else if (current != -1){
                consent [current]--;
        }

        /* include topic if consent level is reached */
        if ((current != -1) && (consent[current] == consentLevel)){
                groupModel.add(current);
        }
        /* take out topic if 2 additional speech acts against it occurred */
        else if ((current != -1) && (consent[current] < (consentLevel - 1))){
                groupModel.remove(current);
        }
}


/**
 * Returns if a topic is included in the group model.
 * @param topic
 * @return true if the topic is included in the group model
 */
public boolean hasGM (int topic){
        return groupModel.has(topic);
}


/**
 * Method to update possibleTopics at the beginning (used by SessionBuilder).
 * @param current
 */
public void set (int [] current){
        possibleTopics = current;
}



/* All methods in the following produce data for charts or evaluation purposes */



/**
 * Produces data for a chart to show how many topics are included in the group model.
 * @return number of topics included in the group model (int)
 */
public int topicsInGM(){
        return groupModel.numberOfTopics();
}
```

```java
/**
 * Produces data for a chart which displays how many of all possible topics (included in the
 * mental models of participants) are included in the group model.
 * @return how many of all possible topics are included in the group model (int)
 */
public double shareOfPossibleTs(){
        int numberOT = groupModel.numberOfTopics();
        int possibleT = 0;

        /* sum up all possible topics */
   for (int i = 0; i < size; i++) {
     if (possibleTopics [i] > 0){
          possibleT++;
     }
   }

        if (possibleT != 0){
                return (double) numberOT/possibleT;
        }
        else {
                return -1; /* Error value if no entries are included in the mental models */
        }
}

/**
 * Number of possible topics (listed in individual mental models at the beginning). Data for
 * evaluation.
 */
public int three(){
        int helper = 0;

   for (int i = 0; i < size; i++) {
     if (possibleTopics [i] > 0){
          helper ++;
     }
   }
   return helper;
}

/**
 * Average number of topics per participant at the beginning.
 * Data for evaluation.
 * @return averageTsPP
 */
public double six () {
        int helper = 0;

        for (int i = 0; i < size; i++){ /* sum up all topics */
                helper += possibleTopics [i];
        }

        /* calculate average */
        return (double) helper / consentLevel;
}

/**
 * Average number of topics per participant at the end.
```

```java
 * Data for evaluation.
 */
@SuppressWarnings({ "rawtypes", "unchecked" })
public double seven (){

        /* get the context and all Participants therein */
        Context context = (Context)ContextUtils.getContext(this);
        IndexedIterable iter = context.getObjects(Participant.class);

        int helper = 0;

        for (int s = iter.size(); s > 0 ; ){ /* all Participants */
                Participant par = (Participant)iter.get(--s);

                for (int j = 0; j < size; j++){
                        if (par.getModel().has(j)){
                                helper++; /* save in overview model for all participants */
                        }
                }
        }

        /* calculate average */
    return (double) helper / consentLevel;
}


/**
 * Average number of participants (for all topics included in the group model) that included
 * a topic in their individual Model at the end which is part of the group model.
 * This is the overlap of mental models and the group model, which can be interpreted as the
 * factual support for the consensus found. Data for evaluation.
 * @return double value
 */
@SuppressWarnings({ "rawtypes", "unchecked" })
public double eight (){

        /* get the context and all Participants therein */
        Context context = (Context)ContextUtils.getContext(this);
        IndexedIterable iter = context.getObjects(Participant.class);

        int helper = 0;

        for (int s = iter.size(); s > 0 ; ){ /* all Participants */
                Participant par = (Participant)iter.get(--s);

                for (int j = 0; j < size; j++){
                        if (groupModel.has(j) && par.getModel().has(j)){
                                helper++; /* save in overview model for all participants */
                        }
                }
        }

        /* calculate average */
        if (groupModel.numberOfTopics() > 0){
                return  (double) helper / (groupModel.numberOfTopics() * iter.size());
        }
        else {
                return -1; /* error value: no topics in the group model */
```

```java
                        }
                }

                /**
                 * Number of topics which have a majority of supporters. Data for evaluation.
                 * @return
                 */
                @SuppressWarnings({ "rawtypes", "unchecked" })
                public int nine (){
                        /* get the context and all Participants therein */
                        Context context = (Context)ContextUtils.getContext(this);
                        IndexedIterable iter = context.getObjects(Participant.class);

                        int helper = 0;

                        for (int j = 0; j < size; j++){
                                int converter = 0;

                                for (int s=iter.size(); s > 0 ; ){ /* all Participants */
                                        Participant par = (Participant)iter.get(--s);

                                        if (par.getModel().has(j)){
                                                converter++;  /* save in overview model for all participants */
                                        }
                                }
                                if (converter > (iter.size() / 2)){
                                        helper++;
                                }
                                converter = 0;
                        }
                        return helper;
                }
}
```

3. Message

```java
package collAct;


/**
 * @author Geeske Scholz
 * Message models speech acts which can be exchanged via discussion. Messages are
 * tuples (speaker, topic, in) and provide getter methods.
 */
public class Message {

        private int identifySpeaker;        /* Identification number of the speaker */
        private int topic;                   /* The current topic */
        private boolean in;                  /* Valuation of the topic: Suggestion to include/exclude
                                                topic in the group model */

        /**
         * Constructor
         * @param pSpeaker identifies the speaker
         * @param pTopic identifies the topic
```

```java
 * @param pIn valuation of the topic to be included/excluded in the group model
 */
public Message(int pSpeaker, int pTopic, boolean pIn) {
        identifySpeaker = pSpeaker;
        topic = pTopic;
        in = pIn;
}

/**
 * Returns the identification number of the speaker (int)
 * @return identification number of the speaker (int)
 */
public int getSpeaker(){
        return identifySpeaker;
}

/**
 * Returns the number of the current topic
 * @return topic number (int)
 */
public int getTopic(){
        return topic;
}

/**
 * Returns Valuation of the topic: Suggestion to include/exclude topic in the group model
 * @return boolean in (the suggestion to include/exclude topic)
 */
public boolean getIn(){
        return in;
}

}
```

4. Model

```java
package collAct;

import java.util.Random;

/**
 * @author Geeske Scholz
 * Model is used to represent the mental models of participants and the resulting group model.
 */
public class Model {

        private int[] graph;        /* topics are saved in an array */
        private int size;           /* number of topics which may be included */

        /**
         * Constructor
         * @param pSize (number of possibly included topics)
         */
        public Model(int pSize) {
                graph = new int [pSize];
                size = pSize;
```

```
    }

/**
 * Adds a new topic to the model.
 * @param i (the topic to be included)
 * @return true if the topic was added
 */
public boolean add (int i){
        if ((i < size) && (i > 0)){
                graph[i] = 1;
                return true;
        }
        else {
                return false;
        }
}


/**
 * Removes topics from the model.
 * @param i (topic to be removed)
 * @return true if topic was removed
 */
public boolean remove (int i){
        if ((i < size) && (i > 0)){
                graph[i] = 0;
                return true;
        }
        else {
                return false;
        }
}


/**
 * Returns a random topic included in the model, and -1 if no topic is included.
 * @return a random topic (int) included in the model, and -1 if no topic is included
 */
public int getRandom (){
        Random rnd = new Random();
        int start = rnd.nextInt();
        int topic = -1;
        /*
         * A random int and the modulo function are used to start a loop at a random location
         * of the array and check whether the respective topic is included.
         */
        for (int j = 0; j < size-1; j++){
                int x = start % (size);

                /* topic included? */
                if (has(x)){
                        /* return this topic */
                        return x;
                }

                /* next topic */
                start++;
        }
```

```java
                /* no topic is included. return -1 */
                return topic;
    }


    /**
     * Method to check whether a topic is included in this model.
     * @param i (topic)
     * @return true if topic i is included in the model, else return false.
     */
    public boolean has (int i){
            if ((i < size) && (i >= 0)){
                    return (graph[i] == 1);
            }
            else {
                    return false;
            }
    }


    /**
     * Returns the number of topics included in the model.
     * @return number of topics (int)
     */
    public int numberOfTopics(){
            int number = 0;
    for (int i = 0; i < size; i++) {
        number += graph[i];
      }
    return number;
    }


    /**
     * Prints graph to the console.
     */
    public void showTopics(){
    for (int i = 0; i < size; i++) {
        System.out.print(" " + graph[i]);
      }
    System.out.println();
    }

}
```

5. **Participant**

```java
package collAct;

import repast.simphony.engine.schedule.ScheduledMethod;
import java.util.Random;

/**
 * @author Geeske Scholz
 * Participants take part in the discussion, interpret last messages, decide whether they want
 * to speak (options) and what they want to say. They are also able to learn their
 * mental model (myModel, referring to the substantive model) and role (referring to the
 * relational model) by updating.
 */
```

```java
public class Participant {

        Random rnd;
        int number;              /* identity */
        Role role;               /* role including perception of others and self */
        double social;           /* social is the probability to behave influenced from the Halo or Asch effect
                                    */
        Facilitator facilitator;  /* Facilitator (holds group model) */
        Model myModel;           /* mental model concerning the issue at stake */
        Discussion discussion;
        double openness = 0.3;    /* openness to topics not included in myModel */
        double insistOut;        /* probability to insist to exclude topics out of the group model again */
        double learningP;        /* learning probability */
        double pm = 0.3;         /* probability to join in a topic also represented in myModel */
        double p = 0.05;         /* probability to bring in a topic not represented in myModel from the
                                            protocol (to be not included in the group model) */


        /**
         * Constructor
         * @param pIdentity
         * @param pDiscussion
         * @param pModel (mental model on the issue at stake)
         * @param pRole
         * @param pSocial
         * @param pInsistOut
         * @param pLearning
         * @param pFacilitator
         */
        public Participant (int pIdentity, Discussion pDiscussion, Model pModel, Role pRole,
                        double pSocial, double pInsistOut, double pLearning, Facilitator pFacilitator){

                number = pIdentity;
                discussion = pDiscussion;
                myModel = pModel;
                role = pRole;
                social = pSocial;
                insistOut = pInsistOut;
                learningP = pLearning;
                facilitator = pFacilitator;
                rnd = new Random();
        }


        /**
         * Learning method. Change of roles depends on the similarity of opinions
         * (if the same topics are propagated). MyModel may also change.
         * The probability for model change is linked to the role.
         * @param content
         * @param speaker
         * @param person
         * @param currentTopic
         * @param currentIn
         */
        void update(double content, int speaker, double person, int currentTopic, boolean currentIn) {
                /* learning part on roles on the assumptions that similarity leads to sympathy */
                if (speaker != number){
                        if ((content == 0.9) && (learningP > rnd.nextDouble())){
```

```java
                                role.changePerson(speaker, true);
                        }
                        else if ((content == 1.0) && (learningP > rnd.nextDouble())){
                                role.changePerson(speaker, false);
                        }
                }
                /* else would present the possibility to update self-perception if desired */

                /* learning part for the models (concept learning). People develop concepts on little
                 * evidence, and tend to stick to these concepts without strong evidence against them.
                 * This is implemented in a way that evidence against concepts has to be ten times stronger
                 * to take them out as the evidence needed to include new concepts. */
                if (!myModel.has(currentTopic)){
                        if(currentIn && ((person * learningP) > rnd.nextDouble())){
                                myModel.add(currentTopic);
                        }
                }
                else if (!currentIn && (((person * learningP) / 10) > rnd.nextDouble())){
                        myModel.remove(currentTopic);
                }
        }


        /**
         * Interprets message concerning the content (if it is included in own model) and concerning
         * the role and calls up update and options.
         * @param m (last message)
         * @return content (in & included = 0.9; out & included = 1.0; else openness)
         * @return person (value out of Role / roleMapping) * (value out of Role / roleMapping) /2
         */
        void interpret(Message m) {
                /* first part interprets message concerning the content */
                double content = openness;
                int currentTopic = m.getTopic();
                boolean currentIn = m.getIn();

                if (currentIn && myModel.has(currentTopic)){
                        content = 0.9;
                }
                else if (!currentIn && myModel.has(currentTopic)){
                        content = 1.0;
                }

                /* second part interprets concerning role of speaker */
                double person = m.getSpeaker();

                if (person >= 0) { /* -1 is the default value */
                        person = role.person(m.getSpeaker());
                        person = (person*person) / 2;
                }

                update (content, m.getSpeaker(), person, currentTopic, currentIn);
                options(currentTopic, currentIn, content, person);
        }


        /**
         * Options decides if the participant wants to speak and what it wants to say. Options calls
         * up role with the resulting message. At the moment all messages are sent to role with a
```

```java
 * speech probability of 0.5, this can be adjusted if wanted.
 * @param topic
 * @param in
 * @param content
 * @param person
 */
void options(int topic, boolean in, double content, double person) {

        /* for already included topics */
        if (facilitator.hasGM(topic)){
                if (myModel.has(topic)){
                        changeTopic ();
                }
                if ((social > rnd.nextDouble()) &&
                        ((person > rnd.nextDouble()) || (discussion.topicShare() > rnd.nextDou-
ble()))){
                        if (discussion.topicShare() >= person){
                                /* Asch effect (go with majority) */
                                changeTopic();
                        }
                        else{
                                /* Halo effect (speak along) */
                                role.speak (new Message (number, topic, in), 0.5);
                        }
                }
                else if (insistOut > rnd.nextDouble()){
                        role.speak (new Message (number, topic, false), 0.5);
                }
                else {
                        changeTopic();
                }
        }

        /* Part for topics not included in group model. */
        else if ((content >= rnd.nextDouble()) ||
                        (person >= rnd.nextDouble())){
                if (content > rnd.nextDouble()){
                        role.speak (new Message (number, topic, true), 0.5);
                }
                else if ((social > rnd.nextDouble()) &&
                                ((person > rnd.nextDouble()) || (discussion.topicShare() >
rnd.nextDouble()))){
                        if (discussion.topicShare()>= person){
                                /* Asch effect (go with majority) */
                                role.speak (new Message (number, topic, true), 0.5);
                        }
                        else {
                                /* Halo effect (speak along) */
                                role.speak (new Message (number, topic, in), 0.5);
                        }
                }
                else {
                        role.speak (new Message (number, topic, false), 0.5);
                }
        }
        else {
                changeTopic ();
```

```
        }
    }

/**
 * This decision tree is called up if the agent wants to bring in a new topic.
 * Depending on the parameters pm and p the most likely topic from the protocol
 * might be chosen (either include or exclude) or a random topic out of myModel.
 */
private void changeTopic(){
        int pt = discussion.mostLikelyTopic();

        if (myModel.has(pt) && (pm > rnd.nextDouble())) { /* -1 (error value) is thrown out */
                if (!facilitator.hasGM (pt)) {
                        Message m = new Message(number, pt, true);
                        role.speak(m, 0.5);
                }
        }
        else if ((pt > -1) && (p > rnd.nextDouble())){
                if ((insistOut > rnd.nextDouble()) || !facilitator.hasGM (pt)) {
                        Message m = new Message(number, pt, false);
                        role.speak(m, 0.5);
                }
        }
        else {
                int topic = myModel.getRandom();

                if ((topic != -1) && (insistOut > rnd.nextDouble() || !facilitator.hasGM (topic))) {
                        Message m = new Message(number, topic, true);
                        role.speak(m, 0.5);
                }
        }
}

/**
 * Step is called up every round and starts the interpret method.
 */
@ScheduledMethod(start = 1, interval = 1.0)
public void step(){
        Message last = discussion.getLast();
        interpret(last);
        }

/**
 * Returns the individual Model of this Participant. Used for evaluation.
 * @return myModel
 */
public Model getModel (){
        return myModel;
}

}
```

6. Protocol

```
package collAct;
```

```java
import java.util.Iterator;
import java.util.LinkedList;
import java.util.Random;

/**
 * @author Geeske Scholz
 * Protocol saves the order of the last n (depending on forget) messages with different topics
 * as well as n possible occurrences for each of these saved messages. For every new topic a
 * ProtocolItem is instantiated which handles new messages with the same topic.
 */
public class Protocol {
        Random rnd;                             /*Random object*/
        LinkedList<ProtocolItem> prot;
        private int forget = 3;                 /* gives the amount of memory capacity */
        private double freqProb = 0.3;          /* multiplier for frequency of a topic (ProtocolItem). Regulates
        choices in mostLikelyTopic. If forget is greater than 3 freqProb needs to be readjusted */

        /**
         * Constructor
         */
        public Protocol() {
                rnd = new Random();
                prot = new LinkedList<ProtocolItem>();
        }

        /**
         * Adding of new messages. Restructures the protocol if needed, and does not allow more than
         * the n (forget) entrances. Double entrances are handled and stored by ProtocolItem.
         * @param m (new message)
         * @return true
         */
        public boolean add(Message m){
                Iterator<ProtocolItem> iter = prot.iterator();

                while (iter.hasNext()){
                        ProtocolItem current = (ProtocolItem)iter.next();

                        if ((int)m.getTopic() == (int)current.getTopic()){
                                prot.remove(current);
                                current.add(m);
                                prot.addFirst(current);
                                return true;
                        }
                }

                prot.addFirst(new ProtocolItem(m));

                if (prot.size()> forget){
                        prot.removeLast();
                }

                return true;
        }

        /**
         * Search for the most probable topic to speak about concerning the protocol. Thereby
```

```
     * the probability for a topic to be chosen depends on the location in the protocol
     * (higher for more recent topics) and the number of entrances per topic.
     * @return topic number (int)
     */
     public int mostLikelyTopic (){
             Iterator<ProtocolItem> iter = prot.iterator();
             int next = -1;       /* before a topic is in the protocol -1 is chosen,
                                                afterwards next is the returned topic */

             if (iter.hasNext()){
                     ProtocolItem first = (ProtocolItem)iter.next();
                     double most = freqProb * first.length();
                     next= first.getTopic();

                     if (most > rnd.nextDouble()){
                             return next; /* first is returned if probability is higher than a random number
*/
                     }

                     for(int i = 1; i < prot.size(); i++){
                             ProtocolItem current = (ProtocolItem)iter.next();

                             if ((freqProb * current.length() / (i + 1)) > rnd.nextDouble()){
                                     /* the current topic is returned if probability is higher than a random
number */

                                     return current.getTopic();
                             }
                             if (most < (freqProb * current.length() / (i + 1))){
                                     /* topic with highest probability is "next" */
                                     next = current.getTopic();
                             }
                     }
             }
             return next;
     }

     /**
     * Returns how many different actors wanted to include a certain topic. It depends on the
     * number of possible entrances (forgetfulness) how many messages on a topic are saved at all.
     * @param topic
     * @return count of different participants that wanted to include the topic
     */
     public int topicCount (int topic){
             Iterator<ProtocolItem> iter = prot.iterator();
             int next = 0; /* before a topic is in the protocol 0 is chosen,
                                                afterwards next is used for the count */

             while (iter.hasNext()){
                     ProtocolItem first = (ProtocolItem)iter.next();

                     if (first.getTopic () == topic){
                             return first.howMany();
                     }
             }
             return next;
     }
```

```java
/**
 * Returns an Iterator object of the Protocol
 * @return Iterator of the ProtocolItems saved in prot
 */
public Iterator<ProtocolItem> getProt(){
        return prot.iterator();
}


/**
 * Inner class for ProtocolItems saved within the Protocol's LinkedList.
 * ProtocolItems consist of a stack of messages, and methods to operate on the stack. If more
 * than forget messages are saved in the ProtoclItem the oldest message is deleted.
 * @author Geeske Scholz
 *
 */
private class ProtocolItem {

        int topic;                      /* topic number */
        int speaker;                    /* identification number of the speaker */
        boolean inP;                    /* the suggestion to include/exclude topic */
        LinkedList<Message> history;

        /**
         * Constructor
         * @param m (Message to be saved)
         */
        public ProtocolItem (Message m){
                topic = m.getTopic();
                speaker = m.getSpeaker();
                inP = m.getIn();
                history = new LinkedList<Message> ();
                history.push(m);
        }

        /**
         * Adds a new entry (message). If afterwards more than forget messages are saved, the
         * oldest one is deleted.
         * @param m (Message to be added)
         */
        public void add(Message m){
                history.push(m);

                if (history.size()> forget){
                        history.removeLast();
                }
        }

        /**
         * Returns the size of history.
         * @return size of history (int)
         */
        public int length(){
                return history.size();
        }

        /**
         * Returns the topic
```

```java
     * @return topic (int)
     */
    public int getTopic(){
            return topic;
    }

    /**
     * Returns how man different actors wanted to integrate a topic (only from the messages
     * saved in history), though the highest possible amount is restricted by forget.
     * This method is used for the Asch effect.
     * @return how man different actors wanted to integrate a topic (int)
     */
    public int howMany(){
            LinkedList<Integer> list = new LinkedList<Integer> ();

            if (inP){
                    list.add(speaker);
            }

            Iterator<Message> iter = history.iterator();

            while (iter.hasNext()){
                    Message m = (Message) iter.next();
                    int lastSpeaker = m.getSpeaker();

                    if (m.getIn() && !list.contains(lastSpeaker)){
                            list.add(lastSpeaker);
                    }
            }
            return list.size();
    }
  }
}
```

7. Role

```java
package collAct;

import java.util.Random;

/**
 * @author Geeske Scholz
 * Role belongs to a participant and provides the roleMapping which saves self-perception and
 * perception of all other participants. Role is used by participant to speak and enforces or
 * weakens speech probability depending on the perceived position in the discussion.
 */
public class Role {

        Discussion dis;           /* Current Discussion */
        double [] roleMapping;    /* perception of other agents and self-perception [0,1] */
        int howMany;              /* number of participants */
        double k = 0.5;           /* proportionality constant for logistic growth function for
                                                    roleMapping update (learning) */
        Random rnd;               /* Random object*/

        /**
```

```
 * Constructor
 * @param pDiscussion
 * @param pHowMany (number of participants)
 * @param pBoss (boolean if the boss setting is activated)
 */
public Role(Discussion pDiscussion, int pHowMany, boolean pBoss){
        rnd = new Random();
        dis = pDiscussion;
        howMany = pHowMany;
        roleMapping = new double [howMany];

        for( int i = 0; i < howMany; i++){
                roleMapping [i] = rnd.nextDouble();

                /* if the boss setting was chosen participant 0 has a 0.5 higher value in all roles */
                if (pBoss && i == 0){
                        roleMapping [i] = Math.min(roleMapping[i]+0.5, 1);
                }
        }
}

/**
 * Reinforces or weakens the probability of speech depending on perception of self and others.
 * May pass message to discussion to speak.
 * @param m (Message)
 * @param prob (speech probability, in this first implementation 0.5)
 */
public void speak(Message m, double prob){
        double groupPerception = 0;

        /* calculate average group perception */
        for ( int i = 0; i < howMany; i++){
                groupPerception += roleMapping [i];
        }

        groupPerception /= howMany;

        /* if group perception higher/lower than own perception enforce/weaken speech probability
         * (logistic, proportional to difference) */
        double amplify = roleMapping [m.getSpeaker()] - groupPerception;
        double t = prob;
        prob = t + (amplify * t * (1 - t));

        /* pass message to discussion to speak with probability prob */
        if (prob > rnd.nextDouble()){
                dis.speak(m);
        }
}

/**
 * @param i number of participant
 * @return double value (roleMappig) for participant i
 */
public double person (int i){
        return roleMapping[i];
}
```

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```java
        /**
         * Learn about participant i with a logistic learning function.
         * Only used if learning is activated.
         * @param person (participant to learn about)
         * @param positive (true if positive perception of the participant grows)
         */
        public void changePerson (int person, boolean positive){
                double helper = k;

                if (!positive) helper = helper * -1;
                double t = roleMapping[person];
                double change = helper * t * (1 - t);
                roleMapping[person] = t + change;

                /* update of the overall representation of roles in the discussion */
                dis.setRole(person, change);
        }

        /**
         * Prints roleMapping to the console.
         */
        public void show(){
    for (int i = 0; i < howMany; i++) {
        System.out.print(i + " is seen as " + roleMapping[i] + "  ");
    }

    System.out.println();
        }
}
```

8. SessionBuilder

```java
package collAct;

import repast.simphony.context.Context;
import repast.simphony.dataLoader.ContextBuilder;
import repast.simphony.engine.environment.RunEnvironment;
import repast.simphony.parameter.Parameters;
import java.util.Random;

/**
 * @author Geeske Scholz
 * SessionBuilder is the class which manages the simulation, reads parameters from the GUI,
 * instantiates the other objects, and places them in a context.
 */
public class SessionBuilder implements ContextBuilder<Object> {

        @Override
        public Context<Object> build(Context<Object> context) {

                Parameters p = RunEnvironment.getInstance().getParameters();/*read parameters from the
GUI*/

                /*parameters */
                int howMany = (Integer)p.getValue("howMany");    /* number of participants */
```

```java
int modelSize = (Integer)p.getValue("ModelSize");  /* capacity of models */
double topicQuantity = (Double)p.getValue("topicQuantity"); /* to what extend are mental
                                              models of participants filled (randomly) */
double social = (Double)p.getValue("social");          /* probability for Halo and Asch effect */
double insistOut = (Double)p.getValue("insistOut"); /* probability to insist to exclude
                                        topics out of the group model again */
double learning = (Double)p.getValue("learning");   /* learning probability */
int endAt = (Integer) p.getValue("endAt");              /* Possibility to set an end point */

RunEnvironment.getInstance().endAt(endAt);

/* Initiate discussion and add to context */
Discussion dis = new Discussion(howMany);
context.add(dis);

/* In this model all topics included in the mental models of participants are saved */
int [] possibleTs = new int [modelSize];

/* Initiate Facilitator and add to context */
Facilitator fac = new Facilitator(dis, modelSize, howMany, possibleTs);
context.add(fac);

/* Initiate agents and add to context, implementation with random mental models */
for( int i = 0; i < howMany; i++){
        Model mm = new Model (modelSize);

        for( int j = 1; j < modelSize; j++) {
                Random rnd = new Random();

                if (rnd.nextDouble() < topicQuantity) {
                        mm.add (j);

                        /* save in overview model for all participants */
                        possibleTs[j]++;
                }
        }

        /* Initiate Role */
        Role role = new Role(dis, howMany, false);

        /* keep track of the roles */
        dis.setRole(role);

        /* Initiate Participants and add to the context */
        Participant par = new Participant(i, dis, mm, role, social, insistOut, learning, fac);
        context.add(par);
}

/* Update possible topics representation of the Facilitator */
fac.set (possibleTs);

return context;
    }

}
```