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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

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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.

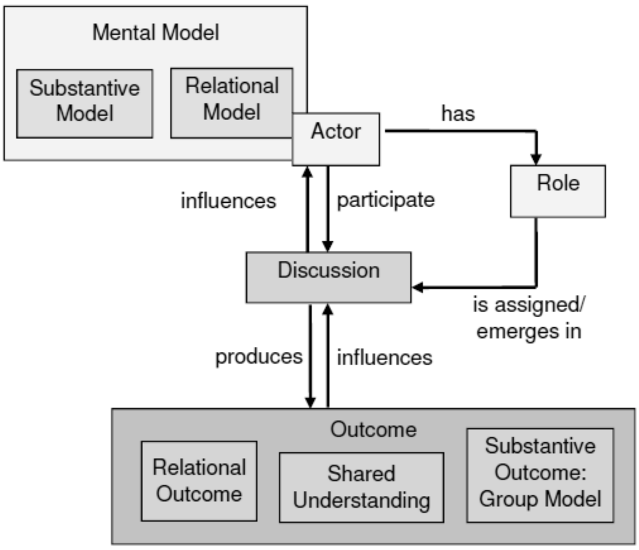

Fig 1. Conceptual framework underlying CollAct, derived from [7]

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 particularly 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

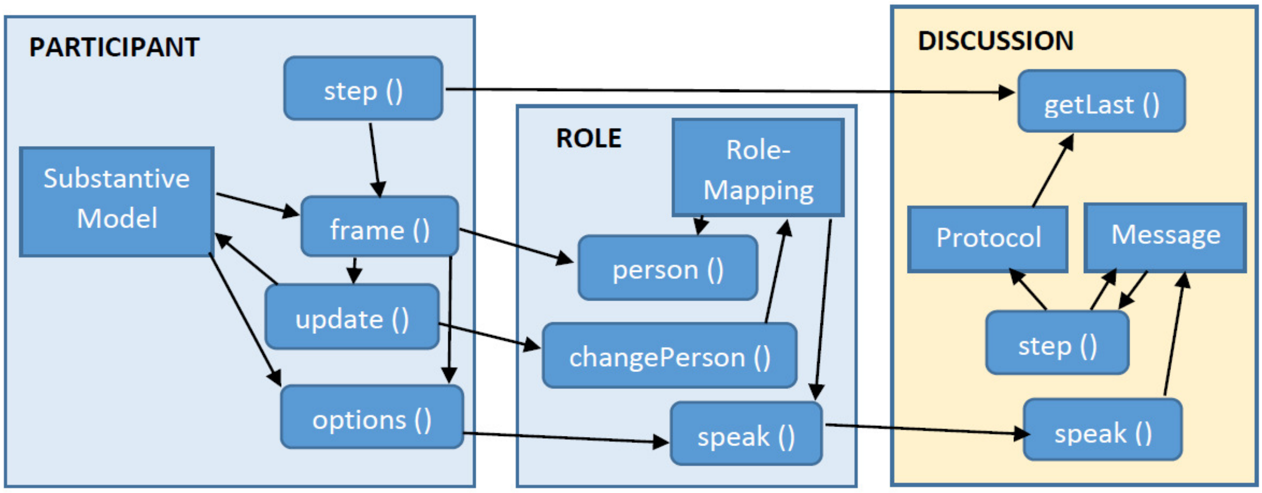

Fig 2. The speech process as modeled in CollAct. Details for participant, role, and discussion are described in the text (type of illustration based on [14])

facilitator sums up all messages in favor and against topics. Hence, in our implementation not all participants have to 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

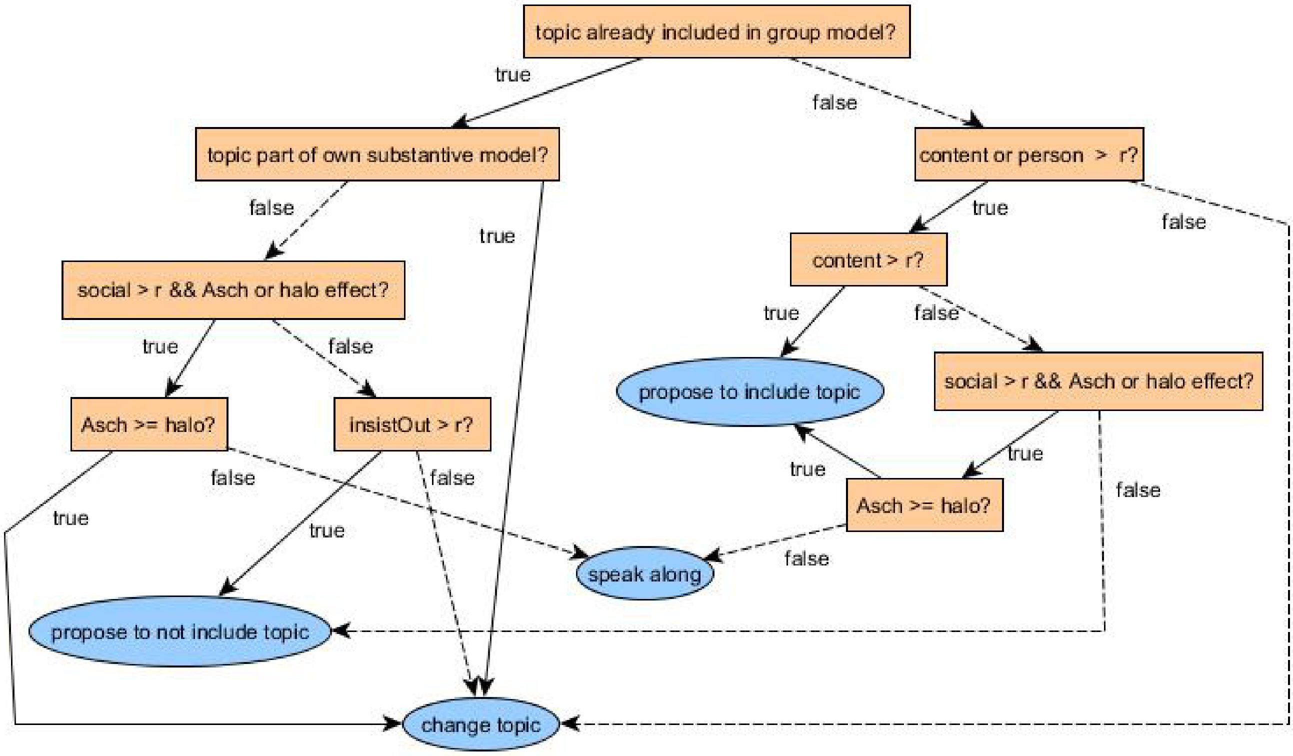

Fig 3. Decision tree in the options method of participant

sending a message. Because CollAct models a turn-taking conversation, only one registered message per step is chosen 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,

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()

this means that the participant is just not interested in what 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.

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

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

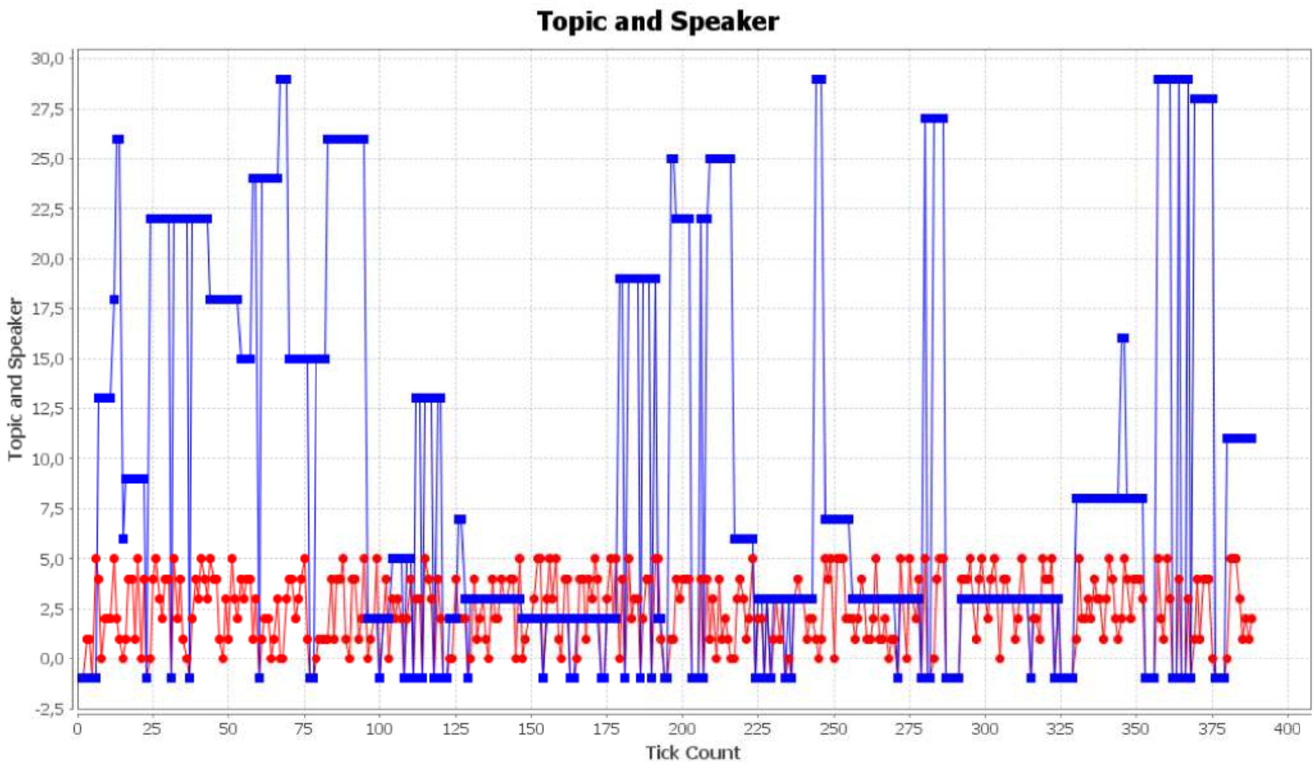

Fig 4. The first part of a run of CollAct. The upper line (blue) represents the topics, while the lower line (red) refers to the speaking participant. As it can be seen, CollAct produces sequences of messages with the same topic, sent from various speakers (participants).

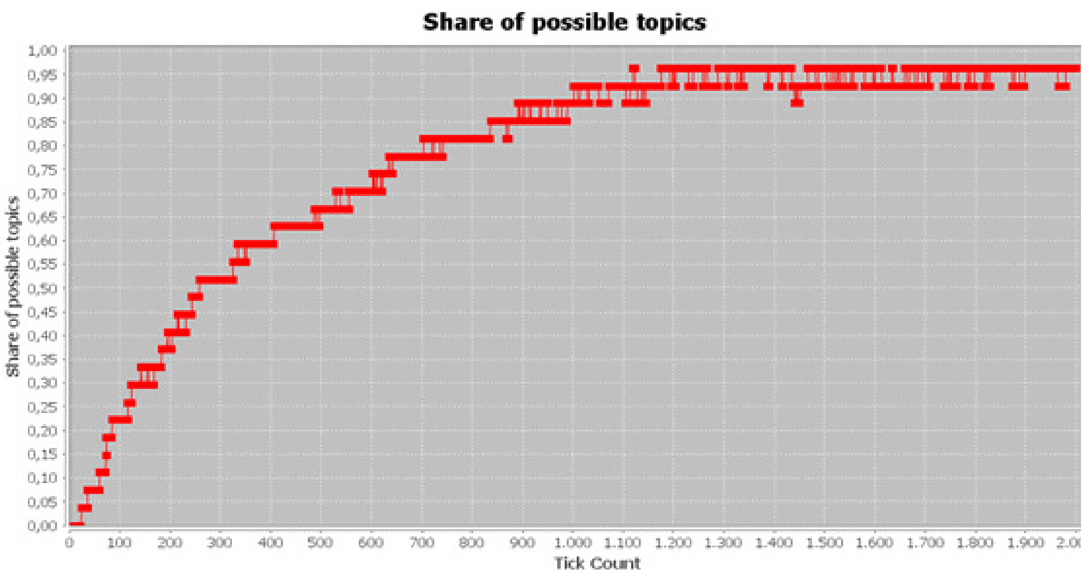

Fig 5. The share of possible topics (of all topics that are represented in the substantive models) in the group model

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

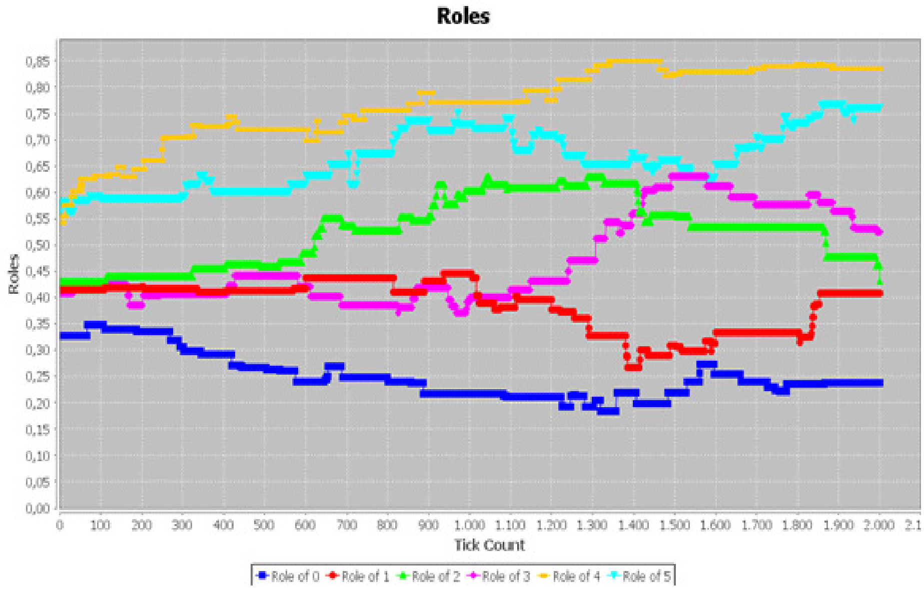

Fig 6. The progress of average roles over time with *insistOut* = 0.1

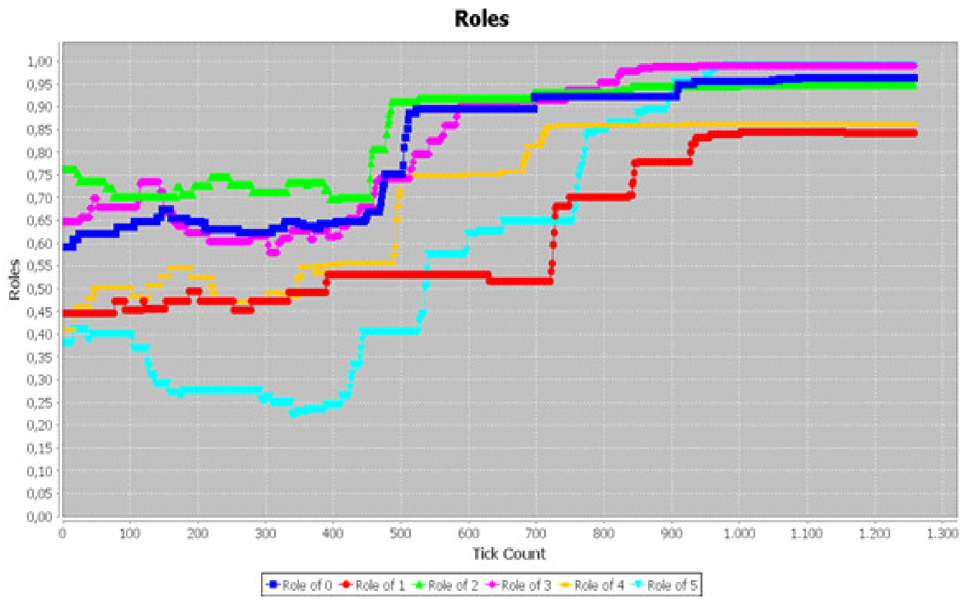

Fig 7. The progress of average roles over time with *insistOut* set to zero

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

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.

References

[1] C. Folke, T. Hahn, P. Olsson, and J. Norberg, "Adaptive governance of social-ecological systems," *Annual Review of Environment and Resources,* vol. 30, pp. 441-473, November 2005

[2] L.C. Stringer, A.J. Dougill, E. Fraser, K. Hubaceck, C. Prell, and M.S. Reed, "Unpacking "participation" in the adaptive management of social-ecological systems: a critical review," *Ecology and Society,* vol. 22, no. 2, pp. 39, 2006

[3] C. Pahl-Wostl, E. Mostert, and D. Tàbara, "The growing importance of social learning in water resources management and sustainability science," *Ecology and Society,* vol. 13, no. 1, pp. 24, 2008

[4] M. Muro, P. Jeffrey, "A critical review of the theory and application of social learning in participatory natural resource management," *Journal of Environmental Planning and Management,* vol. 51, no. 3, pp. 325-344, 2008

[5] G. Raadgever, "Does collaboration enhance learning?," Ph.D. Dissertation, Water Management, TU Delft, The Netherlands, 2009

[6] M. Reed, "Stakeholder participation for environmental management: A literature review," Biological Conservation, vol. 141, no.10, pp. 2417-2431, 2008

[7] G. Scholz, A. Dewulf, C. Pahl-Wostl, “An analytical framework of social learning facilitated by participatory methods,” *Systemic Practice and Action Research,* pp. 1-17, November 2013

[8] J.R. Anderson, *Cognitive psychology and its implications.* New York: Worth Publishers. 2000

[9] D. Dörner, *Bauplan für eine Seele.* Hamburg: Rowohlt. 1999

[10] S. Plous, *The psychology of judgment and decision making.* Mcgraw-Hill Book Company. 1993

[11] S.E. Asch, “Effects of group pressure on the modification and distortian of judgments,” in Group, leadership and men, H. Guetzkow, Ed. Pittsburgh: PA:Carnegie Press, 1951, pp. 177-190

[12] E.L. Thorndike, “A constant error in psychological ratings,” Journal of applied psychology, vol. 4, no. 1, pp. 25-29, 1920

[13] M.J. North, N.T. Collier, J. Ozik, E. Tatara, M. Altaweel, C.M. Macal, M. Bragen, P. Sydelko, “Complex adaptive systems modeling with Repast Simphony,” *Complex Adaptive Systems Modeling,* vol.1, no.3, March 2013

[14] T. Šalamon, *Design of Agent-based Models: Developing Computer Simulations for a Better Understanding of Social Processes*. Tomáš Bruckner, 2011.

[15] K.G. Troitzsch, “Simulating communication and interpretation as a means of interaction in human social systems,” *SIMULATION,* vol. 88, no. 7, November 2010

[16] R Core Team, “R: A language and environment for statistical computing.” *R Foundation for Statistical Computing,* Vienna, Austria, 2013

[17] G. Scholz, M. Austermann, K. Kaldrack, C. Pahl-Wostl, “A method to evaluate group model building sessions by comparing individual concept models and group models,” *System Dynamics Review*, under review

[18] R.S. Baron, N.L. Kerr, *Group process, group decision, group action.* 2nd ed. Berkshire:Open University Press, McGraw-Hill Education. 2003

[19] R. Ison, C. Blackmore, B.L. Ianquinto, “Towards systemic and adaptive governance: Exploring the revealing and concealing aspects of contemporary social-learning metaphors,” *Ecological Economics,* vol. 87, pp. 34-42, March 2013

[20] B. Edmonds, S. Moss, “From KISS to KIDS- an 'anti-simplistic' modeling approach”, *Manchester Metropolitan University Business School Working Paper Series,* September 2005

[21] O. Barreteau, C. Le Page, “Using social simulation to explore the dynamics at stake in participatory research,” *Journal of Artificial Societies and Social Simulation,* vol. 14, no. 4, pp.12, October 2011