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The dynamics of social agreement according to Conceptual Agreement Theory

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Abstract Many social phenomena can be viewed as processes in which individuals in social groups develop agreement (e.g., public opinion, the spreading of rumor, the formation of social and linguistic conventions). Conceptual Agreement Theory (CAT) models social agreement as a simplified communicational event in which an Observer (O) and Actor (A) exchange ideas about a concept C, and where O uses that information to infer whether A's conceptual state is the same as its own (i.e., to infer agreement). Agreement may be true (when O infers that A is thinking C and this is in fact the case, event $a1$) or illusory (when O infers that A is thinking C and this is not the case, event $a2$). In CAT, concepts that afford $a1$ or $a2$ become more salient in the minds of members of social groups. Results from an agent-based model (ABM) and probabilistic model that implement CAT show that, as our conceptual analyses suggested would be the case, the simulated social system selects concepts according to their usefulness to agents in promoting agreement among them (Experiment 1). Furthermore, the ABM exhibits more complex dynamics where similar minded agents cluster and are able to retain useful concepts even when a different group of agents discards them (Experiment 2). We discuss the relevance of CAT and the current findings for analyzing different social communication events, and suggest ways in which CAT could be put to empirical test.

Keywords Conceptual Agreement Theory · Agent-based modeling · Conceptual diversity · Dynamics of conceptual development

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1 Introduction

Many social phenomena can be viewed as processes in which social groups develop agreement (e.g., public opinion, the spreading of rumor, the formation of social and linguistic conventions; Castellano et al. 2009). However, we believe that a general theory of human social agreement is lacking. Such a theory should be useful, not only in the study of phenomena like those discussed immediately above, but also in different basic and applied fields (e.g., sociology, anthropology, psychology, marketing). In the current work, we briefly describe such a theory, implement it in an agent-based model (ABM), and develop a probabilistic model that allows predictions. ABM is a bottom-up simulation tool, in which the researcher embeds the behavior of individuals in computational objects (agents) and the interaction among them creates the aggregate behavior of the system that is under investigation. That is why ABM is so frequently and naturally used in modeling the behavior of groups (Canessa and Riolo 2006; Ball 2003; Arrow et al. 2000). In two ABM experiments, we show the adequacy of the theory's probabilistic formulation and the ABM's compliance to our theoretical assumptions. Finally, we discuss our results vis-à-vis the theory's potential for empirical testing.

Conceptual Agreement Theory (CAT; Chaigneau et al. 2012) aims at being a general theory of human social agreement, in which people agree about the meaning of concepts used in communication events. CAT models an idealized communication event, such as are described by Wittgenstein (1953). In these events, participants talk about something they cannot ostensively define. In Wittgenstein's famous example, people own boxes each with a "beetle" inside, and may talk about the "beetle" but are not allowed to show it to others. According to Wittgenstein, in such a situation, the nature of whatever participants are talking about (e.g., "beetles") is irrelevant to their conversation, and only the pragmatics of language matter (i.e., how they talk in such situations). In fact, according to Wittgenstein, everyone could have different things inside their respective boxes, and yet still talk about their "beetles."

According to CAT, human beings are often in such a situation when talking about abstract entities (e.g., democracy, political views, masculinity, personality traits). However, people often agree or disagree about these things, just as if these things could be ostensively defined or as if there were facts of the matter to be discovered. CAT assumes that what people do in these situations is to infer agreement, i.e., to infer whether other people's mind-content is similar to their own content or not. To illustrate, imagine two individuals, O and A, that are having a conversation about a given topic, and that O has a hypothesis C about how entity x is being jointly conceptualized (i.e., that they are talking about x as an instance of C). However, and just like in the "beetle" example, because concepts are events in individual minds, O can only infer whether C is the case for A or not. To make this inference, O observes A, and when A describes x as having a property of type i, O evaluates if i is consistent with C in her mind or not. If it is consistent, then O infers that A is also talking about x conceptualized as C (otherwise, disagreement is inferred).

Arguably, agreement and communication about abstract concepts is only possible because meaning is conventional, i.e., there is a lawful relation between properties and concepts and there is a limited set of concepts that apply to a given situation (cf., Lewis 1969, 1975; Millikan 2005). In CAT, the conventionality of concepts is unpacked into 4 assumptions: (1) a concept C can be described by a finite set of properties i among a larger but still finite set of possible properties (see e.g., Hampton 1979; Rosch and Mervis 1975; Rosch et al. 1976; Smith 1978); (2) these properties are stable across a social group (see, McRae et al. 2005; Overschelde et al. 2004); (3) these properties are probabilistically related to their concepts; and (4) because entities may be categorized in multiple manners

(D'Lauro et al. 2008; Murphy and Brownell 1985; Patalano et al. 2006; Rogers and Patterson 2007; Rosch et al. 1976), conventionality also imports reducing possible conceptualizations to a small number of alternatives (for simplicity but without losing generality, throughout this paper, only two alternative C and Cn conceptualizations).

In addition to the four abovementioned claims, CAT makes one last critical assumption. CAT assumes that there is between-individual variability in conceptual content for a given concept. CAT assumes that even if individuals in a social group conceptualize an entity similarly, there will be differences between individuals in terms of conceptual content. A simple mechanism that could produce this inter-subjective variability is learning. Because people are exposed to different experiences, it is likely they will end up with somewhat different conceptualizations (for discussions about the implications of variability, see Alvesson 2004; Barsalou 1987, 1993; Converse 1964; Frege 1893/1952; Glock 2009). This variability makes CAT's claim that agreement is a probabilistic inference even more plausible.

The assumptions above conjunctively allow defining a concept C as a set of rather similar conceptualizations that reside in individual minds across a population, that are all conventionally applicable in a given situation, and that share property types to a degree that allows calling them versions of the same concept. The same applies to Cn.

The ABM we report here focuses on two probabilities that represent the aforementioned inferences of agreement. First, the probability of true agreement (symbolized by $p(a1)$), which stands for the probability that two agents (O and A) agree on something given that they have a version of the same concept in their minds. Second, the probability of illusory agreement (symbolized by $p(a2)$), which stands for the probability that O and A agree, given that they hold versions of different concepts in their minds.

Though CAT can handle cases where properties i belong to concept C and Cn following any arbitrary probability distribution, here we limit ourselves to the case of equiprobable or uniform distributions of conceptual properties. For equiprobable cases, we have shown (not included here due to space restrictions) that

$$p\,(a1) = \frac{s_1}{k_1} \tag{1}$$

and that

$$p\,(a2) = \frac{s_1 u}{k_1 k_2} = p\,(a1)\,\frac{u}{k_2}, \tag{2}$$

where k_1 is the total number of properties for a concept C in a population of individuals; s_1 the average number of property types coherent with concept C in an individual's mind ($s_1 \leq k_1$); k_2 the total number of property types in an alternative conventional conceptualization Cn; s_2 the average number of property types coherent with concept Cn in an individual's mind ($s_2 \leq k_2$); u is the number of property types that are consistent with C and with Cn (i.e., the cardinality of the $C \cap Cn$ set).

To illustrate the meaning of these equations, consider the following example, which corresponds to the C and Cn concepts depicted in Fig. 1:

$C = \{a, b, c\}$ $\quad Cn = \{c, d, e, f\}$

$k_1 = 3$, and assuming that $s_1 = 2$ $\qquad k_2 = 4$, and assuming that $s_2 = 3$

$u = 1$ (one common element, i.e., c)

Then using (1) for C,

$$\mathrm{p}\,(a1) = \frac{2}{3}$$

and using (2),

$$\mathrm{p}\,(a2) = \frac{2}{3} \cdot \frac{1}{4} = \frac{1}{6}$$

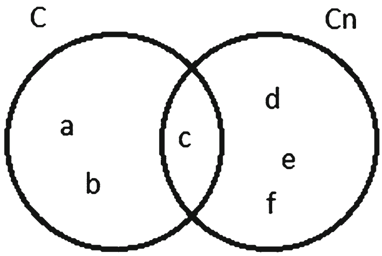

Fig. 1 Two concepts C and Cn with their corresponding i properties and intersection, with $k_1 = 3, k_2 = 4, u = 1$

Consequently, for O and A, the probability that A utters something that for O is consistent with C (allowing the inference that A is really thinking that C), given that A is in fact thinking that C, is 2/3. The same inference but given that A is in fact thinking that Cn, is 1/6. Similarly we can calculate a $p(a1)$ and $p(a2)$ for Cn using (1) and (2) as $s_2/k_2 = 3/4$ and $(s_2u)/(k_2k_1) = (3 \cdot 1)/(4 \cdot 3) = 1/4$.

From (1), it is clear that $p(a1)$ for equiprobable distributions of properties is the number of property types coherent with a version of concept C in an average individual's mind, over the total number of property types available for C in a population of individuals. Thus, $p(a1)$ is a measure of the coherence of a conceptual representation in the minds of members of a social group. The greater this probability, the more likely is that two individuals will find true agreement. From (2), it is clear that $p(a1)$ and $p(a2)$ are interrelated and cannot be assigned arbitrary values. In general, $p(a2)$ will be a fraction of $p(a1)$ that depends on the magnitude of u.

In the philosophy of language the emergence of things such as sets of shared properties and shared contrast categories, has been explained in terms of solving the problem of communicating. Consider Lewis (1969, 1975), for example, for whom conventions arising in language are a way of solving the problem of communicating beliefs. In this view, concepts in a culture are selected according to their capacity to promote social coordination. In the CAT framework, this same idea may be formulated by stating that in a given culture concepts are selected to the extent that they promote inferences of agreement. For example, imagine a concept that is very difficult to learn, such that individuals end up with many different versions of what presumably is the same concept (i.e., $s1 \ll k_1$). This concept would not be maintained by the social group, given that it affords a low probability of true agreement. Similarly, imagine two presumably contrasting concepts C and Cn that share many properties (i.e., $u/k_2 \approx 1$). This pair should not be kept separate in the social group given that it produces a high probability of illusory agreement.

In the following section, we describe an ABM that models a process of concept selection in a social group that is guided by inferences of agreement as earlier described. In keeping with the KISS principle (Axelrod 1997), we tried to implement CAT in the most simple possible way and added details only if deemed necessary. Agents bear in their minds versions of C and Cn concepts and randomly interact with other agents. In each interaction, an agent A offers a property i as evidence of its current conceptual state (which may be C or Cn), and another agent O evaluates if property i is consistent with its own current conceptual state (which also may be C or Cn). Whenever O finds agreement, it increases the salience of its current conceptual state. Whenever O does not find agreement, it decreases the salience of its current conceptual state. Thus, concepts in the simulated social group will be selected or deselected according to their capacity to furnish agreement. Instead of directly manipulating $p(a1)$ and $p(a2)$, as done in Canessa et al. (2011) and Chaigneau and Canessa (2011), here we manipulate the s_1, k_1, s_2, k_2 and u parameters, plus a c parameter that represents the concept's salience in individual agents' minds. This last parameter reflects the effect that agreement has on individuals. In our ABM, experiencing agreement leads agents to (1) increase the strength of their current conceptualization in their minds (our cognitive assumption, cf. Evans 2008; Brewer 1988; Lenton et al. 2001) and (2) to increase their current conceptualization's ability to guide future behavior (our motivational assumption, cf. Rudman and Phelan 2008). To study how these parameters affect a concept's fate in our system (i.e., if it is kept or not by the system), we use a two-pronged approach that combines ABM experiments with a simple probabilistic model based on decision trees that represent the agents' decision rules.

2 Description of the ABM and probabilistic model

At the beginning of a run, the ABM's code creates the C and Cn concepts (similar to the ones illustrated in Fig. 1) by assigning numbers from 1 to k_1 for representing the C's properties and from $k_1 - u + 1$ to $k_1 + k_2 - u$ for designating the Cn's properties. The numbers assigned to the C and Cn properties will overlap by u numbers, which corresponds to the properties that are part of the intersection between C and Cn. Note that in Fig. 1 we used letters instead of numbers, but that is irrelevant. Next, the ABM's code creates N agents, and each of them independently samples s_1 properties from the k_1 properties that belong to concept C and s_2 properties from the k_2 properties that belong to concept Cn. Those samples will represent the different versions of the concepts that will exist in each agent's mind, per CAT's inter-subjective variability assumption. Additionally, the ABM's code assigns to each agent a c and cn coefficient in the [0,1] interval, which represent the initial salience or strength of concepts C and Cn in each agent's mind. The value for c and cn is the same and may be set. After the initialization stage, the ABM's code performs the following actions, which comprise a simulated time step:

(a) From the N agents, randomly select without replacement an Observer agent (O).
(b) O randomly selects an Actor agent (A) from the rest of the $N - 1$ agents.
(c) A acts according to the rules of the decision tree shown in Fig. 2, which in brief means that A will act according to its version of C or Cn, or even might not act at all.
(d) O activates its version of concept C or Cn, or none of them, and then O observes A and changes its c or cn coefficient according to the rules depicted in the decision tree shown in Fig. 3.
(e) Repeat action a through d until all agents have been Observers.

The decision tree for agent A (Fig. 2) means that A may act according to its version of either concept C or Cn (event A A) with probability p(AA), which is equal to the maximum value of the salience of either concept (i.e., if we accept that at any given moment different possible actions form disjoint sets, and that only one action can be performed, then the probability that A will act at all equals the probability that it will act according to its most probable option). Conversely, A may not act with probability equal to 1 − p(AA) (event A NA). If that is the case, A will not act (or utter) any of the properties contained in its sample of C or Cn, which is represented by assigning to variable E the null value. On the contrary, if A acts (event A

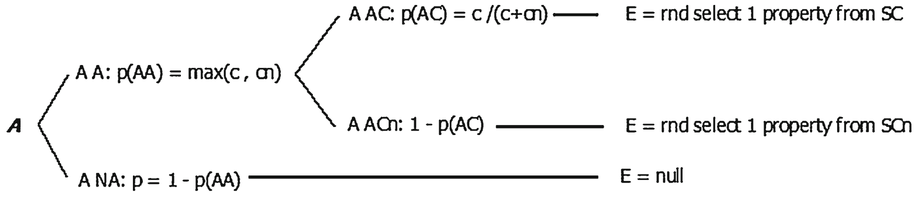

Fig. 2 Decision tree for Actor agent (A)

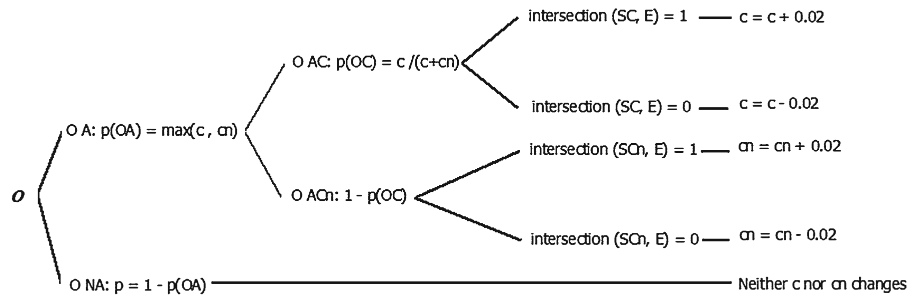

Fig. 3 Decision tree for Observer agent (O)

A), A may do so by uttering a property from C (with probability p(AC)$=c/(c+cn)$, event A AC, i.e., agents choose their conceptual state according to Luce's choice axiom (Luce 1959, 1977); or uttering a property from Cn (with probability $1-$p(AC), event A ACn). In the first case, agent Arandomly selects one property from its sample of C properties (SC) and stores it in E. In event A ACn, agent A selects one property from its sample of Cn properties (SCn) and stores it in E.

After A executes those actions, the O agent behaves according to the decision tree shown on Fig. 3. First, O activates its version of any of the concepts (event O A) with probability p(OA) equal to the maximum value of its coefficient c or cn. Contrarily, O may not activate any of its concepts (event O NA) with probability equal to $1-$ p(OA). If that is the case, according to CAT, O will not change its salience of C and Cn, i.e. its c and cn coefficients will remain the same (i.e., we assume that any conceptual change requires the subject to be explicitly considering a relevant concept; this is not uncontroversial, but discussing this goes far beyond the scope of the current work).

If O activates one of its concepts, then O may activate its version of concept C (event O AC) with probability p(OC)$=c/(c+cn)$, or its version of concept Cn (event O ACn) with probability $1-$ p(OC). The final branches of the decision tree in Fig. 3 simply state the conditions under which the salience of C or Cn may increase or decrease, according to CAT. If there exists a coincidence between the property stored in E (the one A acted) and one of the properties of O's activated version of the C concept (SC), then O's c coefficient will increase by 0.02. In terms of CAT, this models A giving evidence congruent with O's version of concept C (regardless of whether that is true or illusory agreement), and thus increasing the salience of O's version of the C concept in its mind. On the contrary, if there is no coincidence, then A did not furnish O with evidence congruent with O's version of C, and thus according to CAT, the C concept should diminish its salience in O's mind (i.e. the c coefficient will decrease by 0.02). As the decision tree in Fig. 3 shows, the same process happens for concept Cn. Note that we implemented the change in the c coefficient using a

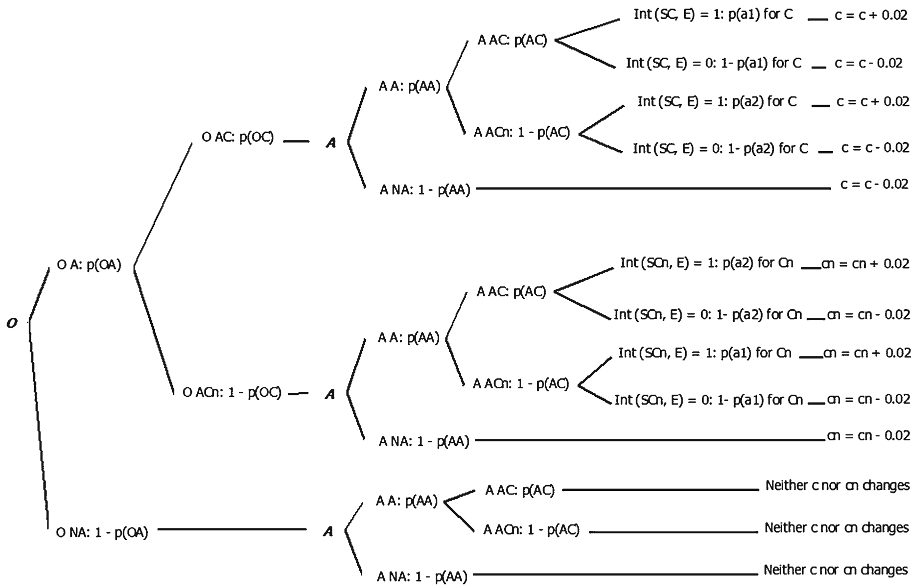

Fig. 4 Combined decision tree for Observer agent (O) and Actor agent (A)

simple linear function, but we experimented with other functions and they did not alter the ABM's dynamics, suggesting that the dynamics are robust to such changes.

To corroborate and better understand the behavior of the ABM, we also developed a simple probabilistic model based on the combination of the decision trees of A and O (see Figs. 2 and 3). Figure 4 shows the combined decision tree. Additionally, that decision tree will allow us to better relate the ABM to CAT's formulation.

The decision tree on Fig. 4 was built from the point of view of an Observer agent. In that tree, the final branches show whether the combined behavior of O and A will bring about an increase or decrease of the salience of concepts C or Cn in O's mind. The final branches labeled with $c = c + 0.02$ represent the strengthening of C, the branches labeled $c = c - 0.02$ represent the weakening of C, and the same follows for Cn.

Beginning at the root of the tree, if O activates its concepts (event O A), it may activate either its version of concept C (event O AC) or concept Cn (event O ACn). Following the first case, if A activates one of its concepts (event A A), it may act (or utter) a property from C (event A AC), which implies that A will store a property belonging to its version of C in E. If there exists a coincidence between E (from A) and SC (from O) (Int(SC, E) $=1$), then A is furnishing O with evidence congruent with O's version of C, and thus c will augment in O's mind. Given that both O and A are thinking of C, that corresponds to true agreement for C, and thus the probability of that event is $p(a1)$ for C. On the contrary if there is no coincidence between SC and E (Int(SC, E) $=0$), A is not giving confirmatory evidence to O and thus c will decrease (i.e., reflecting the effect of disagreement). The probability of that event is $1 - p(a1)$ for C.

Now we need to consider the branch where A activates its Cn concept (event A ACn), which means that A selected one property of its version of Cn and stored it in E. Given that O activated its C concept, that means that the agents will check the intersection between SC and E. If there is a coincidence (Int(SC, E) $= 1$), then A is furnishing O with evidence congruent with O's version of C, and thus c will augment in O's mind. Given that O is instantiating C and A is thinking of Cn, that corresponds to illusory agreement for C, and thus the probability of that event is $p(a2)$ for C. On the contrary if there is no coincidence between SC and E (Int(SC, E) = 0), A is not giving confirmatory evidence to O and thus c will decrease. The probability of that event is $1 - p(a2)$ for C.

Now, at the fork for A, we need to consider that A does not activate any of its concepts (event A NA). Since O activated concept C and A does not activate any of its concepts, then A is not giving confirmatory evidence to O, and thus according to CAT, O's c coefficient will decrease (i.e., though A's actions are relevant, only the state of O is relevant for changes in its conceptual state).

Looking at the decision tree on Fig. 4, one can see that when O activates concept Cn (event O ACn), that part of the tree is the same as the one already explained, but for Cn. Briefly, if A activates one of its concepts (event A A), it may do so with C (event A AC) or Cn (event A ACn). In the first case, if Int(SCn, E) = 1, A is giving confirmatory evidence to O, and thus O's cn will increase. Thus, the probability of that event is $p(a2)$ for Cn (probability of illusory agreement for Cn). In the complementary event (Int(SCn, E) = 0), with probability $1 - p(a2)$ for Cn, O activated its version of Cn and A activated its version of C and because there is no common property between SCn and E, O's cn will decrease. On the other hand, the next two final branches of the decision tree represent the situation in which A activates its Cn concept (event A ACn), and thus depending on whether Int(SCn, E) = 1 (with probability equal to $p(a1)$ for Cn) or Int(SCn, E) = 0 (with probability equal to $1 - p(a1)$ for Cn), O's cn coefficient will increase or decrease. Finally, the next branch corresponds to the event A NA (i.e. A does not activate any of its concepts), in which case O's cn coefficient will decrease.

Going now back to the root of the tree, and considering that O does not activate any of its concepts (event O NA), then no matter what A may do, according to CAT, the salience of the concepts in O's mind will not change (recall our assumption that any conceptual change requires the agent to be explicitly considering a relevant concept).

Having explained the combined decision tree on Fig. 4, we can apply it to build a simple probability model. To do so, we just solve the decision tree. Here we will explicitly calculate the expression for the probability that concept C strengthens (increases its c). The probabilities for the other events that interest us (strengthening of Cn and weakening of C and Cn) are similarly calculated and a thorough development will be omitted due to space limitations. This is a simple probability model given that it strictly holds for the beginning of a simulation run. The probabilities used in Fig. 4 will change during the course of a run, and thus we can straightforwardly calculate them only for that moment. Therefore, we labeled all those probabilities as "initial".

For calculating the initial strengthening probability for C (p(isC)), we must consider the final branches of the tree on Fig. 4, where $c = c + 0.02$, given that for all the other branches, the p(isC) is zero. Solving for p(isC), we get:

$$p\,(isC) = [p\,(a1)\,p\,(AC) + p\,(a2)\,(1 - p\,(AC))]\,p\,(AA)\,p\,(OC)\,p(OA) \tag{3}$$

Remember that in (3), $p(a1)$ and $p(a2)$ are for concept C.

Additionally, to reduce the complexity of the analysis, for this study we assume that $c = cn$ at the beginning of a simulation run, then p(AA) = p(OA) = max(c, cn) = c and p(AC) = p(OC) = $c/(c + cn)$ = 1/2. Under those considerations, (3) reduces to:

$$p\,(isC) = \frac{1}{4}c^2[p\,(a1) + p\,(a2)] \tag{4}$$

As already stated, if we follow a similar procedure, but taking into account the final branches of the tree where $c = c - 0.02$, we can obtain the initial weakening probability for C:

$$p\,(iwC) = [[(1 - p\,(a1))\,p\,(AC) + (1 - p\,(a2))\,(1 - p\,(AC))]\,p\,(AA) + (1 - p\,(AA))]p\,(OC)\,p(OA) \tag{5}$$

And applying the above-mentioned assumptions to (5), it reduces to:

$$p\,(iwC) = \frac{1}{2}c\left[\frac{1}{2}c\,[(1 - p\,(a1)) + (1 - p\,(a2))] + (1 - c)\right] \tag{6}$$

Similarly for *Cn*, we can get:

$$p\,(isCn) = [p\,(a2)\,p\,(AC) + p\,(a1)\,(1 - p\,(AC))]\,p\,(AA)\,(1 - p\,(OC))p(OA) \tag{7}$$

$$p\,(iwCn) = [[(1 - p\,(a2))\,p\,(AC) + (1 - p\,(a1))\,(1 - p\,(AC))]\,p\,(AA) + (1 - p\,(AA))](1 - p\,(OC))p(OA) \tag{8}$$

And applying the above-mentioned assumptions to (7) and (8), they reduce to:

$$p\,(isCn) = \frac{1}{4}c^2[p\,(a1) + p\,(a2)] \tag{9}$$

$$p\,(iwCn) = \frac{1}{2}c\left[\frac{1}{2}c\,[(1 - p\,(a1)) + (1 - p\,(a2))] + (1 - c)\right] \tag{10}$$

We should note that in (3) to (6), $p(a1)$ and $p(a2)$ are the probabilities of true and illusory agreement for C and that in (7) to (10), those probabilities are the ones for *Cn*.

As will be more apparent when we begin to analyze the dynamical behavior of the ABM, in order to predict the fate of concepts C and *Cn* (whether they strengthen or weaken in agents' minds) using the simple probability model, it is more important to calculate the relative value of the strengthening versus weakening probabilities, rather than their absolute values. To do so, we define a strengthening index for C and *Cn*:

$$isC = \frac{p(isC)}{p\,(isC) + p(iwC)} \tag{11}$$

$$isCn = \frac{p(isCn)}{p\,(isCn) + p(iwCn)} \tag{12}$$

Defined in that form, an index above 0.5 will suggest that the concept will probably strengthen and below 0.5 that it will probably weaken. Furthermore, if we sum up (4) and (6), or (9) and (10), we can demonstrate that:

$$p\,(isC) + p\,(iwC) = p\,(isCn) + p\,(iwCn) = \frac{1}{2}c \tag{13}$$

Thus, replacing (13) in (11) and (12), we get:

$$isC = \frac{2}{c}p\,(isC) = \frac{1}{2}c[p\,(a1) + p\,(a2)] \tag{14}$$

$$isCn = \frac{2}{c}p\,(isCn) = \frac{1}{2}c[p\,(a1) + p\,(a2)] \tag{15}$$

Again, in (14) the $p(a1)$ and $p(a2)$ are for C and in (15) they are for *Cn*. The most right-hand expressions in (14) and (15) are obtained by replacing (4) for p(isC) in (14) and (9) for p(isCn) in (15), and reducing terms. The usefulness of (14) and (15) will be appreciated later on.

3 Experiments and results

The present ABM materializes CAT more closely and faithfully than a previous model presented in Canessa et al. (2011) and Chaigneau and Canessa (2011). However, results of that previous model showed that $p(a1)$ and $p(a2)$ were the key parameters that drive the ABM's dynamical behavior. In the original ABM, the experimenter may set those two values at will, which means that $p(a1)$ and $p(a2)$ were exogenous variables. On the contrary, given that CAT's formulation implies that we cannot have arbitrary values for those probabilities (see (1) and (2) and related discussion in the introduction), the present ABM incorporates $p(a1)$ and $p(a2)$ as endogenous parameters that must be realistically set, according to CAT, by establishing values for k_1, s_1, k_2, s_2 and u. Thus, our experimental design considered varying the values for those factors, and leaving constant the number of agents ($N = 100$) and setting $c = cn$ at the beginning of a run, similar to previous performed experiments (Canessa et al. 2011; Chaigneau and Canessa 2011).

Additionally, given that in these new experiments we will change k_1, s_1, k_2, s_2 and those values determine the number of possible versions of concepts C and Cn that might be instantiated by the agents, whereas the number of agents remains constant, we want to assess whether this ratio of potential versions to agents might influence the dynamics of the ABM. For example, if for C, $k_1 = 10$ and $s_1 = 8$, the number of possible versions of C is 45 (10!/8!/2!), and all these versions will probably be instantiated in a given ABM run (i.e., given that the ABM has 100 agents, each version will be on average present about two times). In contrast, if $k_1 = 30$ and $s_1 = 24$, the number of possible versions of C is 593,775 (30!/24!/6!), and not all these versions will be instantiated in a given ABM run (in fact, for this case, on average less than 0.02 % of the possible versions may be represented in the ABM).

3.1 Experiment one

Taking into account these considerations, and as Table 1 shows, the first experiment consisted of 4 combinations of $p(a1)$ and $p(a2)$ which were replicated with different proportional values of k_1, s_1, k_2, s_2 and u to be able to gauge the effect of the number of instantiated versions (as discussed above).

To obtain the 4 combinations of $p(a1)$ and $p(a2)$ for C and Cn, we set different values for parameters k_1, s_1, k_2, s_2 and u, such that values of $p(a1)$ and $p(a2)$ for C and Cn could be equally low for both concepts, intermediate for both, equally high for both, or higher for C than for Cn. This is also reflected in the strengthening indexes (isC and isCn) that correspond to each of the 4 combinations. Now, to obtain the 3 proportional conditions, we simply multiplied k_1, s_1, k_2, s_2 and u in conditions 1 through 4 by a factor of 3 (to obtain conditions 5 through 8) and by a factor of 5 (to obtain conditions 9 through 12). The c and cn coefficients of salience were set to avoid that the system converged prematurely. As can be appreciated in (14) and (15), isC and isCn depend on $p(a1)$ and $p(a2)$ additively, but multiplicatively on c and cn. Therefore, low or high initial values of salience coefficients strongly drive the system towards stably low or high final salience values. The main output of the ABM used to analyze its behavior is the average value of c and cn, computed using the values of those coefficients across agents for each simulation step. From here on, we will refer to that statistics simply as the c and cn coefficient. Additionally, for easy inspection of the dispersion of c and cn values across agents, the ABM's code calculates a histogram of those coefficients.

Table 1 Summary of the experimental conditions, parameter settings and results of the first experiment

	Experimental condition			
	1	2	3	4
k1	10	10	10	10
s1	5	8	9	7
u	4	6	8	8
k2	10	10	10	10
s2	5	7	9	7
c	0.80	0.80	0.80	0.74
No. possible versions	252	45	10	120
	Experimental condition			
	5	6	7	8
k1, s1, u, k2, s2, c	Same as in 1, 2, 3, 4 but k1, s1, u, k2, s2 × 3			
No. possible versions	155,117,520	593,775	4,060	14,307,150
	Experimental condition			
	9	10	11	12
k1, s1, u, k2, s2, c	Same as 1, 2, 3, 4 but k1, s1, u, k2, s2 × 5			
No. possible versions	1.26411E+14	10,272,278,170	2,118,760	2.25083E+12
No. simulated steps	5,000	25,000	5,000	5,000
	Concept C			
p(a1)	0.500	0.800	0.900	0.700
p(a2)	0.200	0.480	0.720	0.560
p(isC)	0.112	0.205	0.259	0.172
p(iwC)	0.288	0.195	0.141	0.198
isC	0.280	0.512	0.648	0.466
	Concept Cn			
p(a1)	0.500	0.700	0.900	0.700
p(a2)	0.200	0.420	0.720	0.560
p(isCn)	0.112	0.179	0.259	0.172
p(iwCn)	0.288	0.221	0.141	0.198
isCn	0.280	0.448	0.648	0.466
	Results (20 replications per condition)			
c coeffs. converge to 1	0 %	100 %	100 %	On avg. 60 %
cn coeffs. converge to 1	0 %	0 %	100 %	On avg. 60 %
Summary	C and Cn consistently converge to 0	C consistently converges to 1 and Cn to 0	C and Cn consistently converge to 1	On avg in 60 % of runs C and Cn converge to 1, and in the rest of the runs to 0

As shown in Table 1, the ABM's behavior closely followed the predictions of the simple probabilistic model (i.e., the isC and isCn values). When isC or isCn were low (roughly below a 0.5 value, see experimental conditions 1, 5, 9 for both *C* and *Cn*, and 2, 6, 10 for *Cn*), the

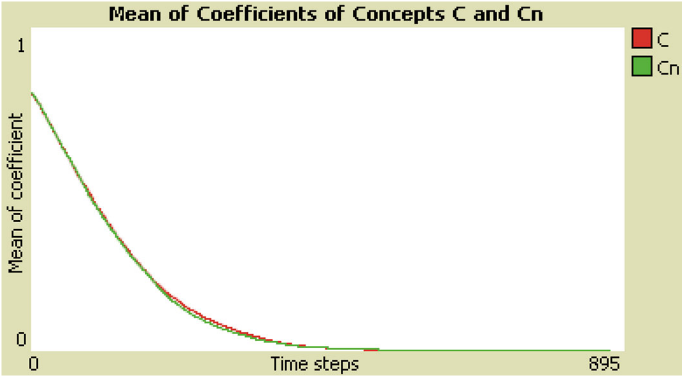

Fig. 5 Average *c* and *cn* coefficients versus simulated time steps for experimental condition 9

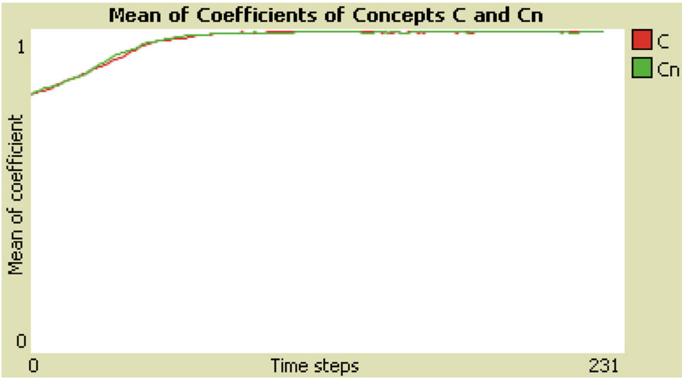

Fig. 6 Average *c* and *cn* coefficients versus simulated time steps for experimental condition 11

corresponding concepts lost salience in agents' minds, reflecting that agents obtained little agreement in their interactions. This dynamics is depicted for a representative simulation run in Fig. 5, which is labeled "convergence to 0".

When isC or isCn were high (see experimental conditions 2, 6, 10 for C and 3, 7, 11 for both), the corresponding concepts increased their salience, reflecting that agents obtained substantial agreement in their interactions, condition which is shown in Fig. 6 and is labeled "convergence to 1". In previous experiments with the original CAT ABM (Canessa et al. 2011; Chaigneau and Canessa 2011), a mixed behavior was also observed, and we were interested in replicating and further exploring it with the current ABM. This is the reason why the *c* and *cn* coefficients in conditions 4, 8 and 12 were set at 0.74. As discussed above, in (14) and (15) isC and isCn depend additively on $p(a1)$ and $p(a2)$ but also on c. Because $p(a1)$ and $p(a2)$ are related and cannot be independently set, achieving intermediate values for isC and isCn may require adjusting c (as we actually did). We will return to these issues in our second experiment. As we expected, when isC and isCn were intermediate (conditions 4, 8 and 12), the ABM exhibited a mixed behavior that reflected the probabilistic process of agents' sampling from C. This dynamics is labeled "split", because in some runs the salience of concepts increases and in others it decreases. Note that under this condition, the fate of C and Cn was always consistent with each other, i.e., in a given run both C and Cn

simultaneously lost or gained salience in agents' minds. Note also that Table 1 shows the number of simulations steps performed by the ABM for consistently achieving steady state. Those figures indicate that the convergence of c and cn is slower for condition 6 and 10 than for the rest. That happens because under those two conditions, the system is less biased toward convergence than under the rest of the initial conditions. In fact, in condition 6 and 10, isC is closer to 0.5 than in the other conditions.

Two conclusions from this first experiment need to be highlighted. First, the ABM's dynamics strongly depend, as predicted by (14) and (15), on $p(a1)$ and $p(a2)$. Second, for a broad range of conditions, the simple probabilistic model is able to account very well for the ABM's behavior, even when the number of effectively instantiated versions by the agent population is only a minuscule fraction of the potentially available versions given the k_1, s_1 and k_2, s_2 parameter values. Note that the number of possible version of concepts presented in Table 1 for each experimental condition increases by a factor of at least 400 and as large as 5×10^{11} between experimental conditions. This means that the influence of $p(a1)$ and $p(a2)$ estimates from (1) and (2) on predicting the fate of concepts is very robust across sampling regimes (i.e., the ratio of potential samples to effective samples), when isC and isCn are low or high. However, the simple probabilistic model is less able to explain the system's dynamics when strengthening indexes are intermediate (see conditions 4, 8 and 12). The second reported experiment aimed at further exploring this region, as explained next.

3.2 Experiment two

In the second experiment, as shown on Table 2, all conditions were in the intermediate range of isC and isCn (for C, isC = 0.467; for Cn, isCn = 0.498) and we varied k_1, s_1, k_2, s_2 and u proportionally. In condition 14, these parameters were increased by a factor of 3, and in condition 15 they were increased by a factor of 5 from the values set for condition 13. The intermediate values for isC and isCn were chosen because they represent those regions of ABM dynamics that are not well explained by the simple probabilistic model.

For condition 13, the salience of Cn converges to 1, which might be expected from an isCn index very close to 0.5 (isCn = 0.498). That might also be expected for C, since its isC index is also close to 0.5 (isC = 0.467). However, the results in Table 2 indicate that at the beginning of a run, the c coefficient increases even above its initial value but then slowly converges to a non-zero value (see Fig. 7). This means that for this condition, C and Cn exhibit a synergistic effect, so that each concept helps the other to survive due to relatively high $p(a2)$ values. Contrary to what happened in experiment one, where the fate of the concepts seems to be rather independent from each other, here we appreciate their interdependence. Note that this synergy is an important prediction of CAT, and that it is satisfying to see it operating in the ABM's behavior.

The histogram in Fig. 8, shows the distribution of the values of the c and cn coefficients across agents. Note that the cn coefficients are located in the right side of the histogram, which means that Cn's salience is consistently high in agents' minds. On the other hand, the c coefficients are dispersed, which means that the non-zero value for the average of c is due to some agents having a high or rather high salience for C and others a low or very low salience. Thus, under condition 13, agents tend to cluster into two groups according to the value of c: one with high values of c (above 0.5) and another group with low values of c (below 0.5).

To understand how this may happen, we measured the intra-agent and inter-agent variability of the C's properties, at the beginning and end of the runs. We computed the intra-agent mean square deviation to assess the intra-agent variability and the inter-agent mean square

Table 2 Summary of the experimental conditions, parameter settings and results of the second experiment

	Experimental condition		
	13	14	15
k1	10	30	50
s1	7	21	35
u	6	18	30
k2	9	27	45
s2	7	21	35
c	0.80	0.80	0.80
No. possible versions	120	14,307,150	2.25083E+12
No. simulated steps		1,000,000	
		Concept C	
p(a1)		0.700	
p(a2)		0.467	
p(isC)		0.187	
p(iwC)		0.213	
isC		0.467	
		Concept Cn	
p(a1)		0.778	
p(a2)		0.467	
p(isCn)		0.199	
p(iwCn)		0.201	
isCn		0.498	
		Results (20 replications per condition)	
c coeffs. converge to 1	on avg. 30 %	0 %	0 %
cn coeffs. converge to 1	100 %	100 %	100 %
Summary	EC 13: C rises for about 1–20 Ksteps above 0.8 and then slowly converges to a non-zero value (about 0.20–0.40). Cn converges to 1 EC 14, 15: C rises for about 100–300 Ksteps above 0.8 and then slowly converges to 0. Cn converges to 1		

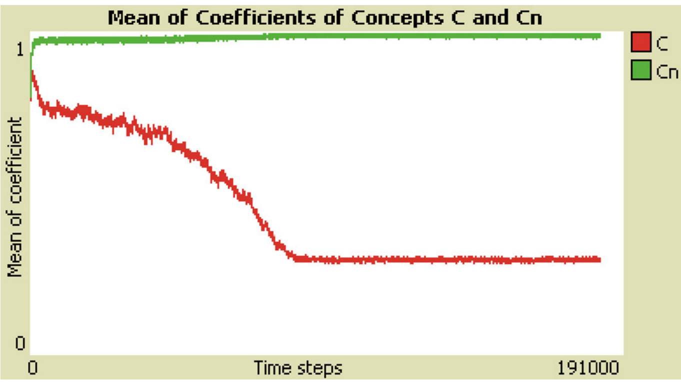

Fig. 7 Average *c* and *cn* coefficients versus simulated time steps for experimental condition 13

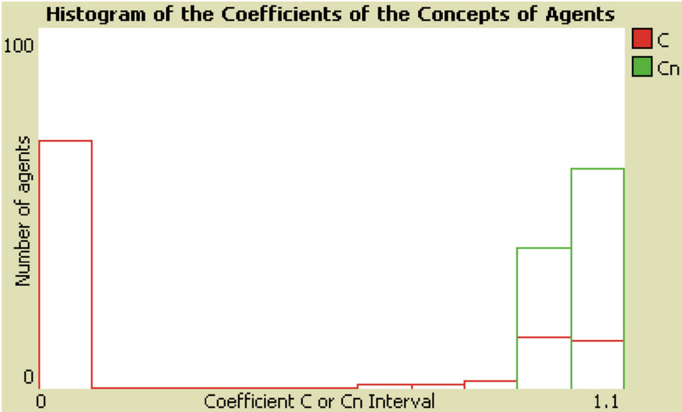

Fig. 8 Histogram of *c* and *cn* coefficients across agents for experimental condition 13 at 190,000 simulated time steps

deviation to measure the inter-agent variability of the C's properties. Note that this procedure is similar to performing a one-factor ANOVA, where the factor is the agent, and thus we can neatly separate both types of variability. The initial intra-agent variability of C's properties at the beginning of a run is 8.960 and the inter-agent variability is 2.845. These figures indicate that at the beginning of the simulation runs for the different versions of C, agents show more diversity within each agent's mind than between them (i.e., conceptual content is very similar across agents). In contrast, at the end of the runs the inter-agent variability for the agents that have a c coefficient above 0.5 shows a reduction to 0.955 and for agents with a c coefficient below 0.5 it also reduces but only to 1.686 (i.e., conceptual content in these final groups becomes more similar across agents). We performed an ANOVA for verifying whether differences between initial and final inter-agent variabilities were significant, obtaining $F(2,1200) = 7.531$ with p value $= 0.001$. Thus, we can conclude that indeed agents cluster into two groups according to the similarity of versions of concept C that they have in their minds. Agents with a relatively low variability tend to form one group, and those agents retain a rather high salience for concept C. Agents with a relatively higher variability (but still lower than in the initial condition) tend to form another group, and those agents loose salience for C.

Note that agents cluster themselves. This behavior emerges from the system and is aligned with CAT's conceptual formulation. A concept which provides agreement among members of a group will be useful for them, and thus will be kept. On the other hand, a concept that does not provide enough agreement will not be useful and will be discarded by the group. In the ABM, we begin with one group of agents, but the dynamics of the system segregates them. Relating this behavior to CAT, it means that a concept may be kept by some group members for whom the concept is useful (because they have similar versions of the concept) and discarded by other members of the group for whom the concept is useless (because they have less similar versions of the concept).

Returning now to analyzing the intra-agent variability, at the end of the runs for agents with a c above 0.5 it also decreased to 8.396 and for agents with a c below 0.5 increased to 9.277. However, the differences between those values and the ones at the beginning of a run are non-significant. That indicates that in general, the variability of concept C in each agent's mind does not change, i.e., the version of an agent's concept will not change, which must be so by the ABM's design: agents sample their conceptual content only at the beginning

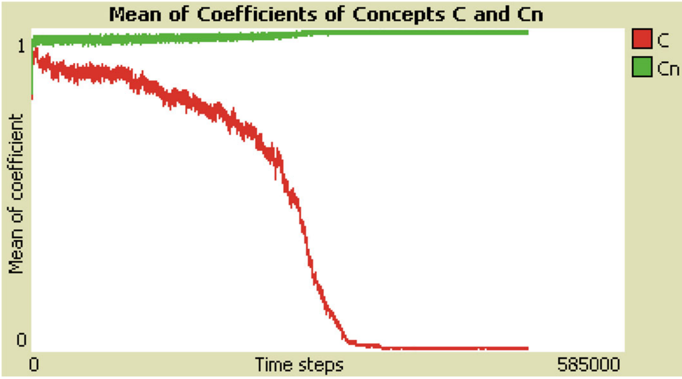

Fig. 9 Average c and cn coefficients versus simulated time steps for experimental condition 15

of a run. Thus, the difference in intra-agent variability remains the same throughout runs. Although this is an expected outcome, it aids in reaffirming the previous conclusions by separating the variability of the versions of concept C into its two components.

Given that in experimental condition 13, the inter-agent concept variability played an important role, and because that variability may be affected by the ratio of possible versions to agents, we replicated condition 13, but increasing k_1, s_1, k_2, s_2 and u, as we also did in experiment one. Table 2 shows that for conditions 14 and 15, although C increases its salience at the beginning of a run, it very slowly converges to zero (see Fig. 9), whereas under condition 13 some agents kept C in their minds. Thus, for experiment two, the diversity of versions of concepts in agents' minds influences the behavior of the ABM. Given that we wanted to understand why diversity influences the dynamics of the system, we compared condition 13 to 15, so that we were analyzing the conditions with the two most extreme diversities. Given that in condition 15 there is no clustering (see Fig. 10), we only computed variabilities at the end of the runs. The inter-agent variability is 60.473; value that is 21.3 times larger than the one for condition 13 (2.845). This is expected, given that the number of possible versions for C increased by a factor of 1.9×10^{10}, which means that agents can sample from a larger set of possible versions. Thus, on average, the versions of C in each agent's mind will tend to be more diverse. Now, the explanation for the different dynamics in conditions 13 and 15 is that the increased diversity in condition 15 will make true and illusory agreement more difficult to achieve among agents and will cause the demise of C, according to CAT's formulation. Under this condition, although there might also be a synergistic effect between C and Cn, given the large diversity among versions of concept C, that effect will not be strong enough to counterbalance the low $p(a1)$ and $p(a2)$ afforded by the very diverse versions of C. In that regard, it is important to note that the values of $p(a1)$ and $p(a2)$ calculated using (1) and (2) assume that all versions of the concepts will be present in a group, but in the ABM, that is not necessarily the case, especially when the ratio of potential versions to agents is very high. In that case, the $p(a1)$ and $p(a2)$ calculated using (1) and (2) will overestimate the actual values present in the ABM. Thus, the indexes isC and/or isCn will be a bad predictor of concepts dynamics, especially when the system is not too biased toward convergence to 1 or 0 (i.e., isC and/or isCn are close to 0.5).

Finally, the simulation steps necessary for the ABM to consistently reach steady state augmented to 1 million steps for experiment two. Comparing that figure with the corresponding ones of experiment one, this represents at least a 40-fold increase. Given that the ABM under

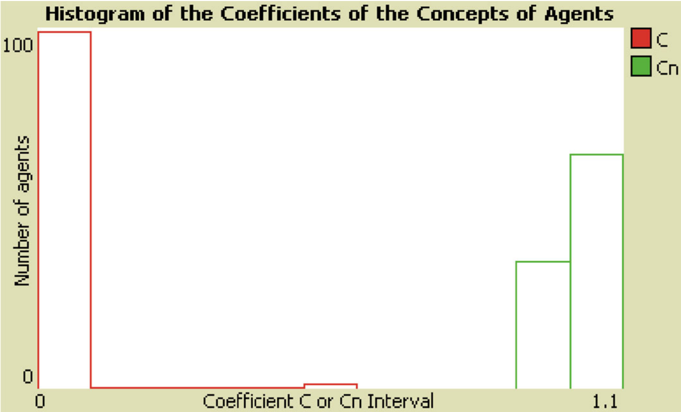

Fig. 10 Histogram of *c* and *cn* coefficients across agents for experimental condition 15 at 500,000 simulated time steps

conditions 13–15 is less biased toward convergence (i.e. the isC and isCn are closer to 0.5), the system needs more time to consistently reach steady state.

4 Discussion

In the current ABM, agents interact and infer agreement, and conceptual states are selected according to their ability to promote agreement among agents (whether true or illusory). The model's assumptions implement the idea that concepts are conventional in social groups, and allow defining probabilities of true and illusory agreement depending on parameter settings. The agents' interaction rules can be expressed as a probabilistic model that enables computing an index, which indicates whether the ABM's initial state promotes the strengthening or weakening of agents' concepts as a consequence of their continued interactions.

In experiment one, results indicate that the simple probability model is able to predict the ABM's dynamics for a wide range of settings, provided that the initial strengthening index is fairly high or fairly low. Under these conditions, as Eqs. (14) and (15) state, the fate of a conventional concept in the simulated social group depends on the concept's initial salience in agents' minds and on its ability to afford true or illusory agreement. These results are straightforwardly derived from the ABM's interaction rules shown in Figs. 2, 3 and 4, and serve to confirm the ABM's steady state behavior. Furthermore, concepts C and Cn appeared to increase or decrease their salience independently from each other, which is in apparent contradiction to CAT's notion that alternative conceptualizations share properties and that illusory agreement may drive the ABM's dynamics. However, this last concern needs to be dispelled because, as Eqs. (14) and (15) show, $p(a2)$ always adds to the strengthening of a concept's salience in agents minds. Recall also that, though in (14) and (15) $p(a1)$ and $p(a2)$ for C and Cn may seem independent, they are really related by parameters k_1, k_2 and u, given that $p(a2)$ for $C = p(a1)$ for C times u/k_2 and $p(a2)$ for $Cn = p(a1)$ for Cn times u/k_1. In fact, conditions 4, 8 and 12 in experiment one illustrate these points. In these conditions, where $p(a1)$and $p(a2)$ were intermediate and symmetrical for C and Cn, and where initial salience was set so that isC and isCn were intermediate, both concepts were linked and followed the same (not independent) fate. A "real world" example that may follow an analogous pattern is the loss of confidence in political parties. This worldwide phenomenon has been explained

(Angell 2003) as the result of the disappearance of Marxism as an ideological alternative and the increasing focus on politicians in general as administrators (in CAT, an increased u parameter and $p(a2)$ probability), and the loss of parties' function as articulators of interests and aggregators of demands that are relevant for individual citizens (in CAT, a reduction of the c coefficient). Under these conditions, CAT would predict an abrupt and joint decrease in the salience of alternative political parties.

Much more interesting behaviors were observed in experiment two. In the second experiment the simple probability model was uninformative about the fate of the concepts, and the system's dynamics was much more nuanced. Several things are noteworthy from those results. First, they show that inter-agent conceptual diversity is intimately related to $p(a1)$. In fact, $p(a1)$ may now be usefully understood as a measure of diversity. When, in experiment two, a high potential versions to agents ratio led to increased diversity, above the diversity implied by the static $p(a1)$ computed value (i.e., an effectively lower $p(a1)$ than estimated), those concepts weakened in agents' minds. A second noteworthy result is that concepts exhibited an intermediate behavior between simply converging to "1" or to "0" as in experiment one. The initially weaker concept in condition 13 (isC = 0.467 in contrast to isCn = 0.489) benefited from a relatively high $p(a2)$ which precluded its fast convergence to "0", in sharp contrast to what was generally observed in experiment one. This illustrates CAT's idea of synergistic effects among related concepts more fully than experiment one. A third noteworthy result is that agents clustered themselves depending on the similarity of the versions of a concept in their minds. This behavior does not follow directly from the interaction rules and is not predicted by the probabilistic model. Given enough time to interact, agents with similar conceptualizations may retain a given concept while agents with less similar conceptualizations may abandon it. In the next paragraph, this clustering process is used to illuminate social phenomena.

Frequently, concepts (even those that have technical meanings) have different senses (like the versions of our *C* and *Cn* concepts). For example, Mayden (1997) discusses 22 different versions of the "species" concept in biology. Like agents with dissimilar conceptualizations, many scholars call for abandoning this concept which they deem useless (e.g., Ereshefsky 2000; Mishler 2000; Pleijel and Rouse 2000a, b). However, like our agents with similar conceptualizations, many other biologists continue to use it because, in one or other of its versions, it is useful for them. In contrast, when the concept in question is value laden (equivalent to a high salience c coefficient in the ABM), a different pattern emerges. Gladwin et al. (1995) list 7 different versions of the "sustainable development" concept. In spite of the obvious parallel with the "species" concept, few if any scholars call for abandoning it (e.g., Robinson 2004, who though being skeptical about the concept, still wants to retain it). Whereas the "species" situation resembles the second experiment, the case of "sustainable development" resembles the first.

Our two experiments show that the CAT ABM exhibits non-trivial behaviors that are in accordance to CAT's theoretical formulation in several respects. Furthermore, the CAT probabilistic model showed the ability to predict the ABM's dynamics over a wide range of settings, allowing us to better understand the theory's implications. Moreover, at this stage of our work, all parameters (i.e., $k1, s1, u, k2, s2$) are possible to estimate for real world situations, and thus the possibility of empirically testing CAT seems within reach. An example of an area where CAT could be tested is the study of *brands* (for other examples, see Canessa et al. 2012; Chaigneau et al. 2012). Firms try to instill brand concepts in the minds of consumers because this relates to consumers' response toward the product and its marketing (Lassar et al. 1995). Though CAT was not initially thought to apply to this topic, a small review of the literature reveals important commonalities. Research about brands is often research about the concepts that people have about brands. Brands are generally described as having properties associated to them, some of which are tangible (i.e., associated with the product's concrete functional characteristics) and others which are intangible (i.e., associated with the product's more abstract characteristics, such as its image) (Keller 2003), and where these properties become associated in consumers' minds, thus creating the meaning of a brand (Aaker 1996; Keller 1993).

Given the aforementioned view about brands, marketers may see their task as crafting a message that conveys the desired brand meaning to consumers. However, the view that brand meaning may be conveyed has been questioned in that, because meaning needs to be shared (or inferred) instead of simply conveyed, consumers have a more active role in determining the meaning of a brand (Keller 2003; McCracken 1986) and many different meanings may exist for the same brand (Berthon et al. 2009). Abundant examples show that when these ideas have been put to empirical test, qualitative methods have been generally used. In Brown et al. (2003), ethnographic methods were used to analyze messages in Web pages and internet news groups discussing people's experiences with well-known brands; in Fournier (1998), in-depth interviews were used to gain insight into individuals' relationships with brands; in Cova and Pace (2006), ethnographic methods were used to analyze an internet community interacting in a company provided Web page; in Nairn et al. (2008), qualitative thematic discourse analysis was used to analyze children's conversations about branded products and to understand their constructed meanings.

Note that much of the discussion above can be encompassed in CAT and quantitatively expressed. Ideas such as that meaning cannot be conveyed but needs to be shared instead, that many different individual meanings for the same concept may exist, and that it is important to consider how people communicate about their experiences with a brand, are all intrinsic aspects of the CAT framework. Thus, we envision the possibility of using brands as a test bed for CAT. For example, given a marketer's desired concept for her brand, we could study whether in a given social group that brand is conceptualized coherently enough to support true agreement, whether associated concepts furnish sufficient overlap to provide the necessary illusory agreement, and that $p(a1)$ and $p(a2)$ are balanced such that the brand concept is useful in conversations.

Summarizing our current work, we have presented an ABM that embodies CAT and represents a social group that selects which conventional concepts to keep depending on their capacity to promote agreement. The ABM exhibits steady state behavior that is well captured by a simple probability model, but also more complex dynamics resulting from the operation of agents' interaction rules in time. The model interestingly illuminates real world phenomena that resemble the simple steady state behavior and the ABM's more complex dynamics. Though the work reported here allows a deeper understanding of the model, it is far from exhausting the complexity of CAT and of the current ABM model. Recall that in the current work we assumed for simplicity that $c = cn$. Relaxing this assumption in future work is one way in which we plan to follow our unfolding of this model's complexities. Finally, and as a way of gaining generality in our analyses, a necessary future step in which we are currently working is to link our work with other independent but convergent lines of research (Marchione et al. 2010; Vogt and Coumans 2003).

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References

Aaker, D.A.: Building Strong Brands. The Free Press, New York (1996)

Alvesson, M.: Knowledge Work and Knowledge-Intensive Firms. Oxford University Press, New York (2004)

Angell, A.: Party change in Chile in comparative perspective. Rev. Cienc. Política **23**(2), 88–108 (2003)

Arrow, H., McGrath, J.E., Berdahl, J.L.: Small Groups as Complex Systems: Formation, Coordination, Development and Adaptation. Sage, London (2000)

Axelrod, R.: Advancing the art of simulation in the social sciences. In: Conte, R., Hegselmann, R., Terna, P. (eds.) Simulating Social Phenomena, pp. 21–41. Springer, Berlin (1997)

Ball, P.: The physical modelling of human social systems. Complexus **1**, 190–206 (2003)

Barsalou, L.W.: The instability of graded structure: implications for the nature of concepts. In: Neisser, U. (ed.) Concepts and Conceptual Development: Ecological and Intellectual Factors in Categorization, pp. 101–140. Cambridge University Press, Cambridge (1987)

Barsalou, L.W.: Flexibility, structure, and linguistic vagary in concepts: manifestations of a compositional system of perceptual symbols. In: Collins, A.C., Gathercole, S.E., Conway, M.A. (eds.) Theories of Memory, pp. 29–101. Lawrence Erlbaum Associates, London (1993)

Berthon, P., Leyland, F.P., Campbell, C.: Does brand meaning exist in similarity or singularity? J. Bus. Res. **62**(3), 356–361 (2009)

Brewer, M.B.: A dual process model of impression formation. In: Srull, T.K., Wyer Jr, R.S. (eds.) Advances in Social Cognition, pp. 1–36. Erlbaum, Hillsdale (1988)

Brown, S.P., Kozinets, R.V., Sherry Jr, J.F.: Teaching old brands new tricks: retro branding and the revival of brand meaning. J. Mark. **67**(3), 19–33 (2003)

Canessa, E., Riolo, R.: An agent-based model of the impact of computer-mediated communication on organizational culture and performance: an example of the application of complex systems analysis tools to the study of CIS. J. Inf. Technol. **21**, 272–283 (2006)

Canessa, E., Chaigneau, S.E., Quezada, A.: An ABM of the development of shared meaning in a social group. In: Proceedings of the 3rd International Conference on Agents and Artificial Intelligence, Rome, Italy, 28–30 January, pp. 5–14 (2011)

Canessa, E., Chaigneau, S.E., Quezada, A.: The life of concepts: an ABM of conceptual drift in social groups. In: Filipe, J., Fred, A. (eds.) Agents and Artificial Intelligence. Communications in Computer and Information Science Series, vol. 271, pp. 271–286. Springer, Heidelberg (2012)

Castellano, C., Fortunato, S., Loreto, V.: Statistical physics of social dynamics. Rev. Mod. Phys. **81**(2), 591–646 (2009)

Chaigneau, S.E., Canessa, E.: The power of collective action: how agents get rid of useless concepts without even noticing their futility. Actas Jornadas Chilenas de Computación, Curicó, Chile 7–11 November pp. 1–8 (2011)

Chaigneau, S.E., Canessa, E., Gaete, J.: Conceptual agreement theory. New Ideas Psychol. **30**(2), 179–189 (2012)

Converse, P.E.: The nature of belief systems in mass publics. In: Apter, D.E. (ed.) Ideology and Discontent, pp. 206–261. The Free Press, New York (1964)

Cova, B., Pace, S.: Brand community of convenience products: new forms of customer empowerment—the case "My Nutella the community". Eur. J. Mark. **40**(9/10), 1087–2005 (2006)

D'Lauro, C., Tanaka, J.W., Curran, T.: The preferred level of face categorization depends on discriminability. Psychon. Bull. Rev. **15**, 623–629 (2008)

Ereshefsky, M.: Species and the Linnaean hierarchy. In: Wilson, R.A. (ed.) Species: New Interdisciplinary Essays, pp. 285–306. MIT Press, Cambridge (2000)

Evans, J.: Dual-processing accounts of reasoning, judgment, and social cognition. Annu. Rev. Psychol. **59**, 255–278 (2008)

Fournier, S.: Consumers and their brands: developing relationship theory in consumer research. J. Consum. Res. **24**(4), 343–373 (1998)

Frege, G.: On sense and reference. In: Geach, P., Black, M. (eds.), Translations from the Philosophical Writings of Gottlob Frege (pp. 56–78). Blackwell, Oxford (1893/1952)

Gladwin, T.N., Kennelly, J.J., Krause, T.S.: Shifting paradigms for sustainable development: implications for management theory and research. Acad. Manag. Rev. **20**(4), 874–907 (1995)

Glock, H.J.: Concepts: where subjectivism goes wrong. Philosophy **84**(1), 5–29 (2009)

Hampton, J.A.: Polymorphous concepts in semantic memory. J. Verbal Learn. Verbal Behav. **18**, 441–461 (1979)

Keller, K.L.: Conceptualizing, measuring, and managing customer-based brand equity. J. Mark. **57**, 1–22 (1993)

Keller, K.L.: Strategic Brand Management: Building, Measuring, and Managing Brand Equity, 2nd edn. Prentice Hall, Upper Saddle River (2003)
Lassar, W., Mittal, B., Sharma, A.: Measuring customer-based brand equity. J. Consum. Mark. **12**(4), 11–9 (1995)
Lenton, A.P., Blair, I.V., Hastie, R.: Illusions of gender: stereotypes evoke false memories. J. Exp. Soc. Psychol. **37**(1), 3–14 (2001)
Lewis, D.: Convention: A Philosophical Study. Harvard University Press, Cambridge (1969)
Lewis, D.: Languages and language. In: Gunderson, K. (ed.) Minnesota Studies in the Philosophy of Science, vol. VII, pp. 3–35. University of Minnesota Press, Minneapolis (1975)
Luce, R.D.: Individual Choice Behavior: A Theoretical Analysis. Wiley, New York (1959)
Luce, R.D.: The choice axiom after twenty years. J. Math. Psychol. **15**(3), 215–233 (1977)
Marchione, E., Salgado, M., Gilbert, N.: 'What did you say?' Emergent communication in a multi-agent spatial configuration. Adv. Complex Syst. **13**(4), 469–482 (2010)
Mayden, R.L.: A hierarchy of species concepts: the denoument in the saga of the species problem. In: Claridge, M.F., Dawah, H.A., Wilson, M.R. (eds.) Species: The Units of Diversity, pp. 381–423. Chapman and Hall, London (1997)
McCracken, G.: Culture and consumption: a theoretical account of the structure and movement of the cultural meaning of consumer goods. J. Consum. Res. **13**, 71–84 (1986)
McRae, K., Cree, G.S., Seidenberg, M.S., McNorgan, C.: Semantic feature production norms for a large set of living and nonliving things. Behav. Res. Methods **37**, 547–559 (2005)
Millikan, R.G.: Language: A Biological Model. Oxford University Press, Oxford (2005)
Mishler, B.: Getting rid of species? In: Wilson, R.A. (ed.) Species: New Interdisciplinary Essays, pp. 307–315. MIT Press, Cambridge (2000)
Murphy, G.L., Brownell, H.H.: Category differentiation in object recognition: typicality constraints on the basic category advantage. J. Exp. Psychol. Learn. Mem. Cogn. **11**(1), 70–84 (1985)
Nairn, A., Griffin, C., Wicks, P.G.: Children's use of brand symbolism: a consumer culture theory approach. Eur. J. Mark. **42**(5/6), 627–640 (2008)
Patalano, A.L., Chin-Parker, S., Ross, B.H.: The importance of being coherent: category coherence, cross-classification, and reasoning. J. Mem. Lang. **54**(3), 407–424 (2006)
Pleijel, F., Rouse, G.W.: A new taxon, capricornia (Hesionidae, Polychaeta), illustrating the LITU ('least-inclusive taxonomic unit') concept. Zool. Scr. **29**, 157–168 (2000a)
Pleijel, F., Rouse, G.W.: Least-inclusive taxonomic unit: a new taxonomic concept for biology. Proc. R. Soc. B **267**, 627–630 (2000b)
Robinson, J.: Squaring the circle? Some thoughts on the idea of sustainable development. Ecol. Econ. **48**(4), 369–384 (2004)
Rogers, T.T., Patterson, K.: Object categorization: reversals and explanations of the basic-level advantage. J. Exp. Psychol. Gen. **136**(3), 451–469 (2007)
Rosch, E., Mervis, C.B.: Family resemblances: studies in the internal structure of categories. Cogn. Psychol. **7**, 573–605 (1975)
Rosch, E., Mervis, C.B., Gray, W.D., Johnson, D.M., Boyes-Braem, P.: Basic objects in natural categories. Cogn. Psychol. **8**, 382–439 (1976)
Rudman, L.A., Phelan, J.E.: Backlash effects for disconfirming gender stereotypes in organizations. Res. Organ Behav. **28**, 61–79 (2008)
Smith, E.E.: Theories of semantic memory. In: Estes, W.K. (ed.) Handbook of Learning and Cognitive Processes, vol. 6, pp. 1–56. Lawrence Erlbaum Associates, Hillsdale (1978)
van Overschelde, J.P., Rawson, K.A., Dunlosky, J.: Category norms: an updated and expanded version of the norms. J. Mem. Lang. **50**(3), 289–335 (2004)
Vogt, P., Coumans, H.: Investigating social interaction strategies for bootstrapping lexicon development. J. Artif. Soc. Simul. **6**(1) (2003). http://jasss.soc.surrey.ac.uk/6/1/4.html
Wittgenstein, L.: Philosophical Investigations. Blackwell, Oxford (1953)