AN ABM OF THE DEVELOPMENT OF SHARED MEANING IN A SOCIAL GROUP

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Keywords: Agent-based modelling, Shared meaning, Conceptual content, Markov chain.

Abstract: Generally, concepts are treated as individual-level phenomena. Here, we develop an ABM that treats concepts as group-level phenomena. We make simple assumptions: (1) Different versions exist of one similar conceptualization; (2) When we infer that our view agrees with someone else's view, we are subject to true agreement (i.e., we really share the concept), but also to illusory agreement (i.e., we do not really share the concept); (3) Regardless whether agreement is true or illusory, it strengthens a concept's salience in individual minds, and increases the probability of seeking future interactions with that person or source of information. When agents interact using these rules, our ABM shows that three conditions exist: (a) All versions of the same conceptualization strengthen their salience; (b) Some versions strengthen while others weaken their salience; (c) All versions weaken their salience. The same results are corroborated by developing probability models (conditional and Markov chain). Sensitivity analyses to various parameters, allow the derivation of intuitively correct predictions that support our model's face validity. We believe the ABM and related mathematical models may explain the spread or demise of conceptualizations in social groups, and the emergence of polarized social views, all important issues to sociology and psychology.

1 INTRODUCTION

Concepts appear to have a life-cycle in the cultures in which they exist. Concepts are born at a certain point in time, spread or not through culture, and die out. Our view here is that the fate of concepts in culture depends on their usefulness, and that a concept is useful when it generates episodes of shared meaning, thus allowing social cohesion and the coordination of behaviour. Given that meaning is something that happens in individual minds, how is it possible that people agree about a meaning? Psychological inquiry often assumes that meaning is shared by resorting to direct reference, i.e., by pointing to the referred object, rather than by describing it (Brennan & Clark, 1996; Brown-Schmidt & Tanenhaus, 2008; Carpenter, Nagell, & Tomasello, 1998; Clark & Krych, 2004; Galantucci & Sebanz, 2009; Garrod & Anderson, 1987; Moses, Baldwin, Rosicky, & Tidball, 2001; Richardson, Dale & Tomlinson, 2009; Tomasello, 1995). Though this approach may work for concrete objects, it does not solve the problem of how people agree about the meaning of diffuse objects (abstract entities like, e.g., democracy, womanhood, happiness). Direct reference does not apply for these objects because they lack clear spatio-temporal limits, thus preventing the use of direct reference in interactions. Furthermore, everyday concepts like those illustrated above are notoriously ill-defined; making shared meaning even more mysterious (Rosch & Mervis, 1975). In our current work, we hold the view that shared meaning is possible because meaning is conventional, i.e., there is a limited set of

Canessa E., Chaigneau S. and Quezada A..
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DOI: 10.5220/0003120100050014
In *Proceedings of the 3rd International Conference on Agents and Artificial Intelligence* (ICAART-2011), pages 5-14
ISBN: 978-989-8425-41-6

meanings that apply to a given situation (Lewis, 1969; Lewis, 1975; Millikan, 2005). Constraining the number of concepts that apply on a given occasion, makes agreement a tractable problem. However, even if a group of people has developed conceptual conventions, the likely case is that each person instantiates a somewhat different version of those concepts (e.g., people may conceptualize "leadership" in slightly different ways). Furthermore, even if a group of people has conventions about more or less dichotomous concepts (e.g., "cowardice" and "courage"), a person could still be wrong about which one is being deployed by someone else at a given moment (e.g., if someone says "suicide", she may be thinking of "cowardice" while I may be thinking of "courage"). Consequently, an individual can never know for sure whether someone else agrees or not with his conceptualization of a given event (even when being explicit). Agreement is a probabilistic inference (Chaigneau & Gaete, in preparation).

The ABM we report here focuses on two probabilities that represent the abovementioned inference. First, the probability of *true agreement* (symbolized by *p(a1)*), which stands for the probability that two agents (an *observer* and an *actor*) agree on something given that they instantiate different versions of the same concept (i.e., the "leadership" example above). Second, the probability of *illusory agreement* (symbolized by *p(a2)*), which stands for the probability that observer and actor agree, given that they instantiate different concepts altogether (i.e., the "courage" or "cowardice" example above).

2 CONCEPTUAL DESCRIPTION OF THE ABM

Our current ABM represents a social group which has a set of conventional conceptual states that, for ease of exposition, we will call the *focal set*. These states can represent different versions of the same concept (e.g., different versions of "leadership"; or a set of closely related concepts, such as "miserly", "stingy", "scrooge"). Our *p(a1)* probability reflects the degree of overlap between the different versions in the focal set (greater overlap implies greater probability of true agreement). Our *p(a2)* probability reflects the degree of contrast against alternative conceptualizations (lower contrast implies greater probability of illusory agreement). The system models the dynamical trajectories of concepts as they become increasingly or decreasingly relevant for agents depending on their capacity to generate agreement of any type.

In each simulation run, agents act as observers and actors. Observers seek evidence that actors share their concept. Actors have a certain probability that they will or will not act according to the focal set concept. If they act according to the focal set concept, that specific interaction has a probability *p(a1)* of providing observers evidence of a shared concept. If actors don't act according to the focal set concept (i.e., they act according to the contrast concept), that specific interaction has a probability *p(a2)* of providing observers evidence of a shared concept.

We make some very simple and quite generally accepted assumptions about our agents' psychology. If the observer witnesses evidence (blind to whether it is true or illusory agreement), then his own conceptual state increases its relevance in his mind (i.e., our cognitive assumption; c.f., Evans, 2008; Brewer, 1988; Lenton, Blair & Hastie, 2002), will be more likely to guide his behaviour in the future (i.e., our motivational assumption; c.f., Rudman & Phelan, 2008), and the observer will want to interact with that particular agent again in the future (i.e., our social assumption; c.f., Nickerson, 1998).

3 ABM IMPLEMENTATION

The theory presented in section 2 is implemented in an agent-based model (ABM). In summary, the ABM represents how concepts spread and get stronger (or weaker) in a social group, by observing the behaviour of other members. In the ABM, each individual is an agent (actor, A), which acts according to its concept with probability equal to the strength of the concept. That behaviour is observed by another agent (observer, O), and that changes the strength of its concept. In general, if the observed behaviour agrees with the behaviour expected from O's concept, then O's concept strengthens. Conversely, if the observed behaviour differs from what is expected from that concept, then O's concept weakens. Concurrently, the agents begin to interact more frequently with those that have strengthened their concepts. In the following paragraphs we describe the details of the ABM.

In the social group that the ABM represents, one can set the number of members that belong to the group. Each agent can have one of five different related concepts or versions of the same concept and each of the concepts or versions is represented by a number in the [0, 1] interval, labelled the *coefficient* of the concept. This coefficient determines the probability that an agent behaves according to the given concept. The initial values of the coefficients are sampled from a normal distribution with a mean and standard deviation, which can be set. The model checks that the assigned coefficients will always remain in the [0, 1] interval.

Agents modify the strength of their concept's coefficients by observing the behaviour of other agents. Every time they see behaviour consistent with their concepts, the corresponding coefficients are incremented by 0.02. On the other hand, if the observed behaviour is not consistent with their concepts, the corresponding coefficients are decremented by 0.02. The model makes sure that the coefficients always remain inside the [0, 1] interval. Thus, when an agent sees that another agent acts according to its concept, it is more probable that the agent will act according to its own concept in the future. These actions spread concepts throughout the group.

Agents develop interaction preferences as they observe each other. Specifically, agents will tend to interact more frequently with agents who have confirmed their concepts in previous interactions, and indirectly, they will be less likely to interact with those that have not confirmed their concepts. This aspect of the ABM limits the diffusion of concepts, given that it imposes certain heterogeneity to the diffusion speed of the concepts. It could even cause the weakening of some concepts among certain members of the group. To simulate this aspect of our theory, each agent has an interaction probability with the rest of the agents. Taking into account computational restrictions, those probabilities take only discrete values (0.08, 0.11, 0.17, 0.26 and 0.38, probabilities which increase by approximately 50% between successive values). At the start of a simulation run, all the agents are assigned a probability equal to 0.08, which means that an agent will randomly interact with any other agent. Then, as the run advances, if agent A confirms O's concept, agent O will increase its interaction probability with A to the immediately larger value. For example, if agent A's interaction probability was 0.08, then agent A will increase that probability to 0.11.

A last aspect incorporated in the ABM is that in a social group, it might exist more than one version of a concept. Thus, the model allows setting the number of versions that will be present in a group between 1 and 5. Each version will be assigned to a number of agents equal to the total number of agents in a group divided by the number of versions.

Each agent O determines whether its concept will strengthen or weaken according to the following rules:

a) If A acts according to its own concept in the focal set, and A's conceptual content completely coincides with O's conceptual content, then O's concept will strengthen with probability equal to 1.

b) If A acts according to its own concept in the focal set, and that concept is a version of the same concept in O's focal set (but not identical), then O's concept will strengthen with probability equal to *p(a1)*and will weaken with probability equal to *1 - p(a1)*.

c) If A does not act according to its concept in the focal set (i.e., acts according to a contrasting concept), and the contrasting concept overlaps somewhat with the O's concept in the focal set, then O's concept will strengthen with probability equal to *p(a2)* and will weaken with probability equal to *1 - p(a2)*.

d) If A does not act according to its concept in the focal set (i.e., acts according to a contrasting concept), and A's conceptual content completely coincides with O's conceptual content, then O's concept will weaken with probability equal to 1.

Finally, each simulation cycle or step of the ABM is composed of the following actions:

i) From the set of all agents, randomly select without replacement an observer agent (O).

ii) O selects one actor agent (A), according to the interaction probabilities that O has for the rest of the agents.

iii) A behaves according to its concept with probability equal to the value of the coefficient of the concept that it has.

iv) O observes that behavior and modifies its coefficient of the concept, according to the rules that were previously described.

v) Repeat steps i) through iv) until all agents have been observers.

We acknowledge that this description may not provide the reader with a complete understanding of our ABM. Space restrictions preclude providing greater detail. In lieu, the ABM is available as a zip file. The interested reader can download it from http://www.uai.cl/images/stories/CentrosInvetigacio n/CINCO/CAT_1_English.zip. To run it, you will need first to install Netlogo version 4.0.4 (http://ccl.northwestern.edu/netlogo/). Once on the ABM interface, do the following steps to run a simulation: (1) Input the simulation parameters, be it with the slider controls or typing the desired p(a1) and p(a2) values in the appropriate windows. (2) Press SETUP. (3) Press SIMULATE. (4) If you want to pause a run, simply press SIMULATE (you will need to press it again to resume).

4 PRELIMINARY RESULTS

Once the ABM was implemented and verified, we carried out several runs to assess the dynamics of the coefficients of the concepts that emerged. After gaining some insights into the dynamics of those coefficients and how different combination of parameters changed those dynamics, we performed experiments fixing the value of some parameters as follows: number of agents = 100; number of versions of a concept (or number of related concepts) = 5; initial value of coefficients of concepts = 0.5; and changing the value of *p(a1)* and *p(a2)* between 0.1 and 0.95. According to the combination of values for *p(a1)* and *p(a2)*, three different dynamics emerged.

4.1 Convergence to Zero

When we set small values for *p(a1)* and *p(a2)*, for example *p(a1)* = 0.1 and *p(a2)* = 0.2, then the coefficients rapidly decrease and get close to zero, remaining at that value. This can be seen in Figure 1, where we plotted the mean value of the coefficient of each version of the concept (c1 through c5) over simulation steps. The mean value of each coefficient is calculated by averaging the individual value of the coefficient of the agents that have each version of the concept.

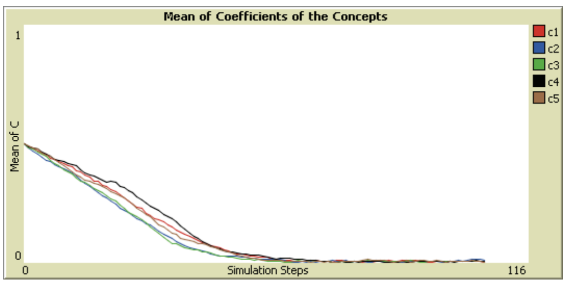

Figure 1: Mean of coefficients of concepts (c1 through c5), for *p(a1)* = 0.1 and *p(a2)*= 0.2.

That happens because the probability that O observes a behaviour consistent with its concepts is very low, since *p(a1)* and *p(a2)* are small. Thus, in general, concepts tend to weaken, which in turn makes it more probable that the coefficients will keep decreasing throughout the run. Conceptually, this is equivalent to concepts that are not useful to generate agreement in a social group, and rapidly die out.

4.2 Convergence to One

When both *p(a1)* and *p(a2)* are set to large values, for example *p(a1)* = 0.8 and *p(a2)* = 0.9, then the coefficients quickly increase and take values close to 1.0. This can be seen in Figure 2.

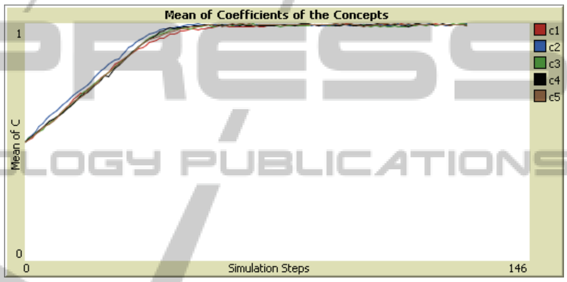

Figure 2: Mean of coefficients of concepts (c1 through c5), for *p(a1)* = 0.8 and *p(a2)* = 0.9.

Contrary to what happened in 4.1, in this situation *p(a1)* and *p(a2)* are large, thus favouring that O observes a behaviour consistent with its concepts, which will strengthen the coefficients. In turn, this makes more probable that in successive cycles, all the coefficients of the concepts will increase. Conceptually, this is equivalent to a group of related concepts synergistically increasing their relevance by promoting agreement in culture.

4.3 Bifurcation

Using different combinations for *p(a1)* and *p(a2)*, such as (0.20, 0.80), (0.60, 0.40), (0.80, 0.16), we saw that some concepts tended to strengthen and others to weaken. We labelled this type of dynamic a "bifurcation", which is shown in Figure 3.

Under this condition, a relatively large value of *p(a1)* or *p(a2)*, but not of both of them, will promote that on each run some Os observe behaviours consistent with their concepts. However, since *p(a1)* or *p(a2)* will have a small value, it will also happen that on each run some Os will not observe behaviours consistent with their concepts. Thus, some versions of the concept will strengthen and others weaken in agents' minds. Conceptually, this is equivalent to a group of related concepts that have a weakly contrasting (i.e., somewhat overlapping) conceptual alternative, such as might be the case of concepts of *male* versus *female* gender, and concepts of *liberal* versus *conservative* political views. Concepts like these tend to become polarized in large social groups, just as occurs in our model's bifurcations.

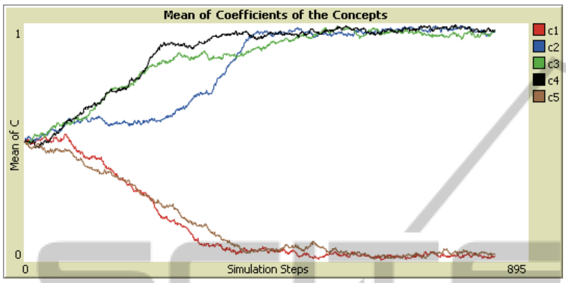

Figure 3: Mean of coefficients of concepts (c1 through c5), for *p(a1)* = 0.2 and *p(a2)*= 0.8.

4.4 Map of Dynamics

Since we realized the significant influence of *p(a1)* and *p(a2)* on the type of dynamics that emerged, we ran simulations using more combinations for these two variables. The types of dynamics of the coefficients that emerged are presented in Figure 4.

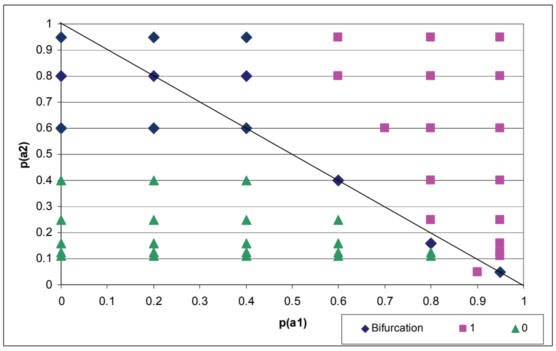

Figure 4: Dynamics that emerge for coefficients of concepts, according to values set to *p(a1)* and *p(a2)*(bifurcation, 1 = convergence to 1, 0 = convergence to 0).

We confirmed that for small values of *p(a1)* and *p(a2)*, we obtained convergence to zero; for large values of *p(a1)* and *p(a2)*, we saw convergence to one; and for other combinations of those parameters, we observed a bifurcation. Interestingly, note that the combinations for *p(a1)* and *p(a2)*, for which we obtain a bifurcation, approximately lie on a line connecting the lower right corner of the graph with the upper left one. Moreover, see that the zone where we get the bifurcation gets wider at the upper left corner. That means that at the lower right corner (*p(a1)* >> *p(a2)*), the dynamics of the ABM gets more sensitive to the combination of *p(a1)* and *p(a2)* than at the opposite corner (*p(a1)* << *p(a2)*). Since that behaviour of the ABM was quite intriguing, we developed another model to try to explain such behaviour.

5 PROBABILISTIC AND MARKOV CHAIN MODEL

To begin to validate the ABM results, and more formally explain the conditions under which the three dynamics appeared, we developed a simple probabilistic model. This initial model justified why the bifurcation emerged when the values for *p(a1)* and *p(a2)* roughly lie on a line connecting the lower right corner of the graph with the upper left one, as shown in Figure 4.

5.1 Simple Conditional Probability Model

To explain the three different types of dynamics that emerge from the ABM, we use a simple conditional probability model to calculate an initial probability that a concept will strengthen (p_{if}). If p_{if} is small, then most probably, the coefficient, which represents the concept, will decrease. On the other hand, if p_{if} is large, the coefficient will increase. If p_{if} is about 0.5, then we obtain the ideal situation under which a bifurcation might occur, i.e. each coefficient will have a 50% chance of decreasing and a 50% chance of increasing, thus making it possible that about half of them will diminish and half of them will augment. Figure 5 shows a conditional probability tree that helps calculate p_{if}.

In this model, p_{if} depends on whether an agent A (actor) behaves according to its concept (event BC), which has probability equal to the initial value of the coefficient that we set (c_0), or not (event NBC, with probability $1 - c_0$). Then, if A acts according to its concept, then there is a p_i probability that A and O share all their conceptual content (event SACC), and a $1 - p_i$ probability that they don't share it all (i.e., each has a different version of the same concept, event NSAAC). If they share all their conceptual content (with probability *pi*), then it is certain that O will strengthen its concept's coefficient. If they share versions of the same concept (with probability

$1\text{-}p_i$), then it is less than certain ($p(a1)$) that O will strengthen its concept.

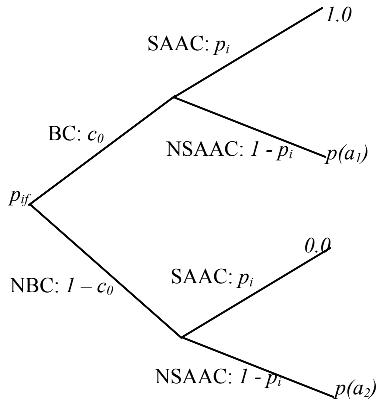

Figure 5: Conditional probability tree for calculating p_{if}.

On the other hand, if A does not behave according to its concept (event NBC), and A and O share all their conceptual content (event SAAC, with probability p_i), then O's concept will certainly weaken. Alternatively, if A and O do not share all their conceptual content (event NSAAC), then it might happen that A provides O with some portion of the conceptual content, and thus O's concept might strengthen with probability $p(a2)$.

Solving the probability tree of Figure 5 for p_{if}, we obtain:

$$p_{if} = c_0[p_i + p_{a1}(1 - p_i)] + (1 - c_0)(1 - p_i)\, p_{a2} \tag{1}$$

In (1), remember that p_i corresponds to the probability that agents share all their conceptual content, i.e. that they have the same version of a concept. Thus, we can calculate p_i for the beginning of a run. In such initial condition, we will have N/V agents with the same version of a concept, where N equals the total number of agents and V is the number of different versions of a concept. Then, the initial probability that agent O will interact with an agent A that has the same version of the concept will be equal to the number of other agents that have the same version as O has (without counting O), divided by the total number of agents (without counting O):

$$p_i = \frac{\frac{N}{V} - 1}{N - 1} \tag{2}$$

For the value of the parameters used in the runs, N = 100 and V = 5, so that p_i = 19/99 = 0.1919.

Now, if we set $p_{if} = 0.5$ in (1), i.e. the ideal condition for obtaining a bifurcation, and establish c_0 = 0.5 (the value we used in our simulation runs), we can get equation (3), which states the ideal condition for $p(a1)$ and $p(a2)$ for getting a bifurcation.

$$p_{a1} + p_{a2} = 1.0 \tag{3}$$

Note that (3) does not contain p_i, which means that that condition applies for any value of p_i. Equation (3) corresponds to a line with an intercept with the y axis ($p(a2)$ axis) equal to 1.0 and slope equal to -1.0, which coincides with the line depicted in Figure 4 that represents the combinations of $p(a1)$ and $p(a2)$ where we obtained a bifurcation. Now, if the sum of $p(a1)$ and $p(a2)$ is bigger than 1.0, we obtain a parallel line to (3), but located above (3). In that case, p_{if} is larger than 0.5, and thus most probably the coefficients will converge to one. This coincides with the region of combinations for $p(a1)$ and $p(a2)$, shown on Figure 4, where the coefficients converge to one. To see that, we can rewrite (1), replacing c_0 = 0.5:

$$p_{a1} + p_{a2} = \frac{2p_{if} - p_i}{1 - p_i} \tag{4}$$

If we replace in (4) p_i for its value 0.1919 and, for example, set p_{if} = 0.6, we obtain $p(a1) + p(a2)$ = 1.248. On the other hand, if the sum of $p(a1)$ and $p(a2)$ is smaller than 1.0, we also obtain a parallel line to (3) but located below (3). In this case, p_{if} will be smaller than 0.5, and thus we will get a convergence to zero of the coefficients. For example, if we put p_{if} = 0.4 in (4), we get the line $p(a1) + p(a2)$ = 0.753. That line is located within the region of combinations of $p(a1)$ and $p(a2)$ shown in Figure 4, where we obtain that dynamic.

However, from Figure 4, we can also see that on the upper left corner of the graph, the line $p(a1) + p(a2) = 1.0$ does not represent all the combinations of $p(a1)$ and $p(a2)$ where the ABM exhibits the bifurcation. Thus, the simple probability model only partially explains the empirical results.

5.2 Markov Chain Model

Since the model in 5.1 calculates p_{if} only for the initial state of a simulation run, it cannot fully capture the dynamical nature of the ABM. Remember that the concepts' coefficients change during a run, as well as the interaction probabilities among agents. In the ABM, that means that c_0 and p_i

will change as the simulation run advances. Thus, we need to build a model that captures that dynamical aspect of the ABM. To do so, we use a simple Markov chain, with four states, as described in Table 1.

Table 1: State transition probability matrix of the Markov chain.

	S_{t+1} $(j = 0)$	W_{t+1} $(j = 1)$
S_t $(i = 0)$	p_{if}^{+}	$1 - p_{if}^{+}$
W_t $(i = 1)$	p_{if}^{-}	$1 - p_{if}^{-}$

Table 1 indicates that if a concept strengthens (state S_t $(i = 0)$), then the probability that it will increase in the next step (state S_{t+1} $(j = 0)$) is p_{if}^{+}, and that it will weaken is $1 - p_{if}^{+}$ (state W_{t+1} $(j = 1)$). On the other hand, if a concept weakens (state W_t $(i = 1)$), then the probability that it will strengthen in the next step (state S_{t+1} $(j = 0)$) is p_{if}^{-} and that it will weaken (state W_{t+1} $(j = 1)$) is $1 - p_{if}^{-}$. In the ABM, each of those p_{if} has a meaning. From expression (1), we know that p_{if} depends on c and p_i, which change during a simulation run. The description of the ABM states that if a concept strengthens, then its coefficient will increase by a certain Δc, and the same will happen with p_i, which will increase by Δp_i. If the concept weakens, then the coefficient c will decrease by Δc, but p_i will remain the same. Therefore, using those facts, we can write the following expressions for p_{if}^{+} and p_{if}^{-}:

$$p_{if}^{+} = p_{if}(c^{+}, p_i^{+}) \text{ with } c^{+} = c_0 + \Delta c,\ p_i^{+} = p_i + \Delta p_i \quad (5)$$

$$p_{if}^{-} = p_{if}(c^{-}, p_i^{-}) \text{ with } c^{-} = c_0 - \Delta c,\ p_i^{-} = p_i \quad (6)$$

Then, replacing (5) and (6) in (1), we can write the explicit equations for p_{if}^{+} and p_{if}^{-}:

$$p_{if}^{+} = (c_0 + \Delta c)[(p_i + \Delta p_i) + p_{a1}(1 - p_i - \Delta p_i)] + (1 - c_0 - \Delta c)(1 - p_i - \Delta p_i)p_{a2} \quad (7)$$

$$p_{if}^{-} = (c_0 - \Delta c)[p_i + p_{a1}(1 - p_i)] + (1 - c_0 + \Delta c)(1 - p_i)p_{a2} \quad (8)$$

Now, if we apply the properties of an ergodic Markov chain (c.f. Ross, 1998), we can compute a long-run probability that a concept will strengthen (Π_0):

$$\Pi_0 = \frac{p_{if}^{-}}{1 + p_{if}^{-} - p_{if}^{+}} \quad (9)$$

Since (9) is written in terms of p_{if}^{+} and p_{if}^{-}, which in turn are given by (7) and (8), it would be rather cumbersome to write an explicit equation for (9) in terms of c, Δc, p_i, Δp_i, $p(a_1)$ and $p(a_2)$. Thus, we prefer to use the following definitions and write a simpler expression for Π_0:

$$\begin{aligned} a &= (c_0 - \Delta c)p_i & e &= (c_0 + \Delta c)(p_i + \Delta p_i) \\ b &= (c_0 - \Delta c)(1 - p_i) & f &= (c_0 + \Delta c)(1 - p_i - \Delta p_i) \\ d &= (1 - c_0 + \Delta c)(1 - p_i) & g &= (1 - c_0 - \Delta c)(1 - p_i - \Delta p_i) \end{aligned} \quad (10)$$

Then, using (10), we can write:

$$\Pi_0 = \frac{a + b\,p_{a1} + d\,p_{a2}}{1 + a + b\,p_{a1} + d\,p_{a2} - e - f\,p_{a1} - g\,p_{a2}} \quad (11)$$

Expression (11) can be rearranged so that it looks similar to equation (4), i.e. represents a line that states the relationship that must exist between $p(a1)$ and $p(a2)$ for a given Π_0:

$$p_{a2} = \frac{b + \Pi_0 f - \Pi_0 b}{\Pi_0 d - \Pi_0 g - d}\, p_{a1} + \frac{a + \Pi_0 - \Pi_0 a + \Pi_0 e}{\Pi_0 d - \Pi_0 g - d} \quad (12)$$

Note that (12) is an equation of a line with a slope equal to the expression located to the left of $p(a1)$ and an intercept with the y axis ($p(a2)$ axis) equal to the far right hand expression. If we compare (12) with (4), we can see that the slope in (4) does not change, depending on the values that $p(a1)$, $p(a2)$ and p_{if} take; but in (12) the slope changes (remember that p_{if} in (4) is equivalent to Π_0 in (12)). Moreover, if we set in (10), $c_0 = 0.5$, $p_i = 0.1919$, $\Delta c = 0.45$ and $\Delta p_i = 0.05$; and put the values a through g, defined in (10), in (12), we can get a family of lines that represents the condition that must meet $p(a1)$ and $p(a2)$ for obtaining different values of Π_0. Figure 6 shows the same graph presented in Figure 4, but displaying lines for $\Pi_0 = 0.3$ to 0.7 according to the Markov chain model that corresponds to expression (12).

From Figure 6, we can see that the line for $\Pi_0 = 0.5$ (the ideal condition for getting a bifurcation) approximately coincides with a line equal to the one we calculated for the simple probabilistic model (see expression (3) and Figure 4). The other lines for $\Pi_0 = 0.6$ and 0.7 are located in the region where the ABM exhibits the convergence to one dynamic and the lines for $\Pi_0 = 0.3$ and 0.4 lie in the region where the convergence to zero dynamic emerges. Thus, we can see that the Markov chain model represents fairly well the conditions under which the ABM exhibits the three different dynamics. Moreover, note that the lines tend to converge toward the lower right corner of the graph, where *p(a1) >> p(a2)* and tend to diverge toward the upper left corner, where *p(a1) << p(a2)*. This means, that the region where we get the bifurcation and which separates the areas where we obtain the convergence to one and zero, gets narrower when *p(a1) >> p(a2)* and wider when *p(a1) << p(a2)*. That characteristic was the one that the probabilistic model described in 5.1 was not able to capture.

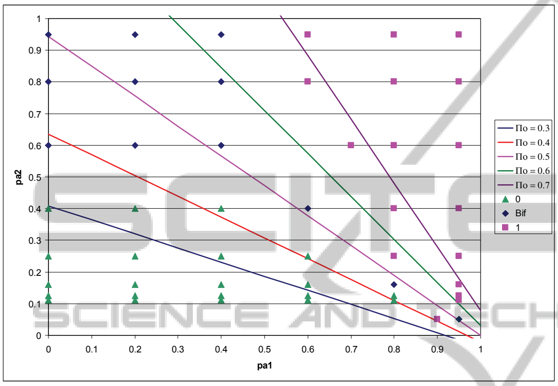

Figure 6: Dynamics that emerge for coefficients of concepts, according to values set to *p(a1)* and *p(a2)*(bifurcation, 1 = convergence to 1, 0 = convergence to 0) and lines for different values of Π_0 according to the Markov chain model.

5.3 Sensitivity of Models to Changes in Values of some Parameters

By analyzing the ABM's and its associated probabilistic models' sensitivity to different parameters, we are able to derive predictions for "real world" situations. Although the Markov chain model presented in 5.2 better explains the dynamical properties of the ABM than the probabilistic model described in 5.1, the latter model is easier to analyze from a substantive point of view. Thus, based on expression (1), we will compute the sensitivity of that model to changes in values of some parameters. Here, we will present only two results of such analyses. To do so, we use (1) and take the partial derivatives of p_{if} with respect to *p(a1)* and *p(a2)*:

$$\frac{\partial p_{if}}{\partial p_{a1}} = c_0(1-p_i) \tag{13}$$

$$\frac{\partial p_{if}}{\partial p_{a2}} = (1-c_0)(1-p_i) \tag{14}$$

Additionally, since p_i appears in (13) and (14) and that variable depends on the number of agents and concepts (*N*, *V* see (2)), we can express (13) and (14) in terms of *N* and *V*. Moreover, given that for reasonably large values of *N*, p_i tends to *1/V*, we will analyze (13) and (14) taking into consideration that $p_i \approx 1/V$.

From (13) and (14) we can see that the sensitivity of p_{if} with respect to *p(a1)* and *p(a2)* is always positive (remember that $0 \le c_0, p_i \le 1$), i.e. the larger *p(a1)* and *p(a2)*, the larger p_{if}. Now, the larger the number of concepts a group has (*V*), the smaller p_i will be and the more influential *p(a1)* and *p(a2)* will be on the value that takes p_{if}. That means that for groups with a large set of related concepts (or many different versions of the same concept), the probability of true and illusory agreement (*p(a1)* and *p(a2)*) will greatly influence p_{if}. The significance of that influence will also be determined by the value of c_0. Note that for large values of c_0, *p(a1)* will have a larger influence on p_{if} than *p(a2)* and vice-versa. Thus, for groups with many concepts, the degree of agreement, either true or illusory, and the initial strength of each concept will dictate whether each concept strengthens or weakens, and eventually disappears.

Several "real world" situations could conform to the dynamics described above. As an illustration, imagine a social group that has an abstract concept, such as *conservative*. Presumably, people would have many different versions of such concept (i.e., a small p_i), with some people, e.g., considering that conservative is a view about economics, while others considering that it is a view about values, and so on. Imagine, furthermore, that this concept's relevance in that society is moderate, in the sense that it does not persistently determine people's actions (i.e., $c_0 \neq 1$). For concepts like this, our sensitivity analyses predict that their fate as a cultural phenomenon will depend mainly on their capacity to generate agreement.

Imagine, furthermore, that *conservative* has *liberal* as a weakly contrasting alternative concept (liberal is weakly contrasting to conservative because it does not clearly divide political opinion in two sharply contrasting clusters). Our sensitivity analyses predict that the fate of this pair will depend on agreement, regardless of whether it is true (*p(a1)*) or illusory (*p(a2)*). Additionally, as discussed in 4.3 above, these conditions promote bifurcations akin to social polarization.

Perhaps, an even more interesting situation arises in groups that have a small number of concepts or versions of them. In that case, p_i will be large, and thus *p(a1)* and *p(a2)* will not have a large influence on p_{if} (i.e., the degree of true and illusory agreement will not have a large influence on the fate of the concepts). Examining Figure 5, we can see that in the above mentioned situation, the fate of each concept will be predominantly dictated by its initial strength c_0, i.e., an initially rather strong concept will disseminate throughout the group and become stronger, and an initially quite weak concept will die out. Note that since in this situation, agreement of any type is almost irrelevant, that implies that a concept may spread even if people do not share the same meaning of it.

Again, a "real world" situation that could conform to these conditions is the following. Imagine a social group in which an authority (moral, political, or other) pushes an oversimplified concept (e.g., a slogan), and creates the conditions to make it relevant (e.g., punishes dissent). As occurs with commands, slogans may leave little room for alternative interpretations (i.e., p_i is large), which, by equations (13) and (14) implies that agreement ceases to be the predominant force that drives that concept's path. In other words, if an authority presents a very simple idea that allows little room for alternative interpretations, and succeeds in making it relevant in people's minds (i.e., makes c_0 sufficiently large), that condition will be sufficient to strengthen the concept and disseminate it throughout the social group, regardless of whether its meaning is shared or not.

6 CONCLUSIONS

In the work we report here, we use our ABM to develop a complex theory about the dynamics of shared meaning in social groups. This use of ABMs is not new, and has been advocated by Ilgen and Hulin (2000). Our ABM embodies some very simple rules of interaction, in keeping with Axelrod's (1997) KISS principle. However, the ABM's dynamics are not simple, as attested by the expanded region of combinations of *p(a1)* and *p(a2)* in Figure 4, where bifurcations emerge.

Our theory development approach to Agent Based Modeling led us to formalize the dynamics through increasingly refined probabilistic models. Not only is this currently allowing us to recursively improve our ABM, but it also allowed us to clearly link the conceptual and mathematical formulations of our theory (respectively, sections 1 and 2, and section 5), and to gain a more general and clear understanding of the ABM's dynamics.

It is true that our model is, at this point, purely theoretical, and that it requires data to support it. However, we incorporated into the ABM generally accepted psychological theory, and as our sensitivity analyses in 5.3 show, the ABM makes intuitively correct predictions that were not built into it in an ad hoc fashion. These two aspects, we think, are at least evidence of the ABM's face validity. We would be very disappointed if future work shows that this validity is only illusory.

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