THE ASSOCIATION BETWEEN GROUP SIZE AND COMMUNICATIONAL COMPLEXITY ACCORDING TO CONCEPTUAL AGREEMENT THEORY

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ABSTRACT

We model the evolution of concepts, i.e. how members of a social group associate properties to concepts. Our Agent Based Model (ABM) is based on Conceptual Agreement Theory (CAT), which states that individuals can only infer the conceptual state of others when communicating. Through communication agents develop a conceptual structure which is influenced by three variables: the size of the group, the number of possible properties that may describe each concept and the rate at which agents learn. In general, the results show that these three variables non-linearly interact and that the larger the group and number of available properties, and the slower the learning process, the richer the conceptual structure that emerges from agents' interactions.

INTRODUCTION

Robin Dunbar has argued that there is a direct relation between the complexity of social systems and the complexity of the communicative systems that regulates their interactions (i.e., the social complexity hypothesis; Dunbar 1993; Freeberg et al. 2012). Dunbar and his collaborators define complex social systems as those in which individuals frequently interact with many different individuals, and define complex communicative systems as those that contain a large number of structurally and functionally distinct elements (Freeberg et al. 2012). However, communication is not nearly as well defined. In their writings, communication relates to phenomena as different as signaling, sharing information, and classifying individuals into types. In contrast to these outlooks on communication, we have argued elsewhere that communication, at least in humans, can be advantageously viewed as the process of using concepts to infer shared mental content, i.e., to infer agreement (Canessa and Chaigneau 2013; Chaigneau et al. 2012). Our first goal in the current work is to provide computational evidence for the social complexity hypothesis starting from our own framework about communication, and to test its capacity to generate novel insights and hypothesis that relate group size and the complexity of the conceptual structure used in communication (i.e., the number of independent structural elements).

When studied in actual social groups, concepts used in language have several interesting properties: (1) Concepts used in language can be sufficiently described by a finite set of properties *i* among a larger but still finite set of possible properties (Hampton 1979; Rosch and Mervis 1975; Rosch et al. 1976; Smith 1978); (2) These conceptual properties are stable in time (McRae et al. 2005; van Overschelde et al. 2004); (3) Though 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), nouns in language offer only a limited number of alternative conceptualizations for entities; (4) The aforementioned conceptual properties are only probabilistically related to their concepts (Chang, et al. 2011; McRae et al. 2005; Wu and Barsalou 2009); (5) Even if individuals in a social group conceptualize an entity similarly, there are differences between individuals in terms of conceptual content, i.e., there will be intersubjective variability (for discussions about variability, see Barsalou 1987, 1993; Converse 1964).

The first three properties probably reflect the conventionality of concepts encoded in language. If these properties were not true, inferring other people's mental content would become an intractable problem. The fourth and fifth properties, particularly the last one, have created difficulties for researchers and thinkers on the topic. The problem may be summarized in the question of whether we can still say that concepts are shared given that there are no necessary relations between properties and concepts, and given that there is variability in conceptual content from one person to the other (Barsalou 1987, 1993; Converse 1964; Frege 1893/1952; Glock 2009).

Finally note that the above discussion of communication according to CAT implies that meaning is inferred instead of just effortlessly and transparently transmitted among people. Thus, our approach substantially departs from traditional psychological and sociological research on social influence and opinion dynamics such as Social Impact Dynamics (Latane 1996), segregation (Schelling 1978), and group dynamics (McGrath et al. 2000; Vallacher et al. 2002). All that work ignores the nuances

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of meaning inference and takes for granted communication among individuals. Although our focus in this paper is Dunbar´s social complexity hypothesis (Dunbar 1993; Freeberg et al. 2012), we think that if our results show that analyzing such ideas using CAT offers new insights, then it would be fruitful to apply CAT to reassessing the traditional work on social influence and opinion dynamics, unpacking the transfer of meaning. That could be done by adding to those models, a new layer of meaning inference according to CAT´s ideas, which we will present in the next section.

CONCEPTUAL AGREEMENT THEORY

Agreement is an important aspect in the analysis of many social phenomena, such as public opinion, the spreading of rumor, the formation of social and linguistic conventions (Castellano et al. 2009). Conceptual Agreement Theory (CAT; Chaigneau et al. 2012; Canessa and Chaigneau 2013) models an idealized communication event where participants talk about something they cannot ostensively define (i.e., something they can't point to). Note that many conversational topics would conform to this description, such as beliefs, opinions, situations not currently in perception, and abstractions. We label these as diffuse concepts. 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. The idealized structure of such conversations is the following. Imagine two individuals, *O* and *A*, that are having a conversation about a given entity. Individual *O* believes that the entity is being jointly conceptualized as an instance of concept *C*. Because in principle *A*'s mental content is private, *O* can only infer whether it is true that the entity is also an instance of *C* for *A* or not. To make this inference, *O* observes *A*, and when *A* describes the entity as having a property of type *i*, *O* evaluates if *i* is consistent with *C* in his mind or not. If it is consistent, then *O* infers that *A* is also talking about the given entity conceptualized as *C* (otherwise, disagreement is inferred).
Though it may not be immediately apparent, because of properties four and five discussed above, these inferences of agreement are necessarily probabilistic. Furthermore, if people carried out conversations following the idealized structure of conversation outlined above, they would sometimes be in true agreement (event *a1*) but at other times they would be in illusory agreement (event *a2*). CAT allows the computation of the probabilities for these two kinds of agreements.
These probabilities are conceptually defined as follows. First, the probability of true agreement (symbolized by *p(a1)*) 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)*) 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 (by property four), in this introduction we limit ourselves to the case of equiprobable or uniform distributions of conceptual properties. This case should allow the reader to understand CAT's basic ideas (for a more in depth discussion, we refer the reader to Canessa and Chaigneau 2013, and Chaigneau et al. 2012).
For equiprobable cases, we have shown (not included here due to space restrictions) that for concept *C*:

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

and that

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

where,

k_1 = 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 = the number of property types that are consistent with *C* and with *Cn* (i.e., the cardinality of the $C \cap Cn$ set).

To help the reader understand the application of expressions (1) and (2) to compute *p(a1)* and *p(a2)*, let's imagine the two concepts depicted in Figure 1, where concept *C* includes properties 0 to 4, and concept *Cn* includes properties 3 to 6, with properties 3 and 4 belonging to both concepts.

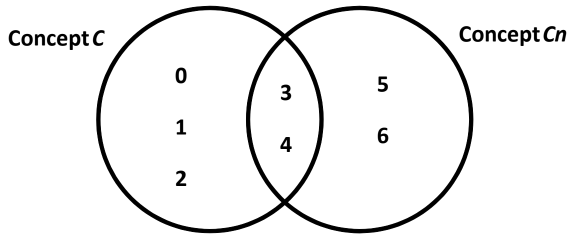

Figure 1: Two Concepts *C* and *Cn* with Their Respective Properties

From Figure 1, we can see that $k_1 = 5$, $k_2 = 4$ and $u = 2$. Assuming that $s_1 = 3$ and $s_2 = 2$, then applying expressions (1) and (2) for concept *C*, *p(a1)* = 3/5 = 0.6 and *p(a2)* = (3/5) (2/4) = 3/10 = 0.3. Similarly for concept *Cn*, the probability *p(a1)* = s_2/k_2 = 2/4 = 0.5 and *p(a2)* = (s_2/k_2) (u/k_1) = (2/4) (2/5) = 1/5 = 0.2. The meaning of these probabilities is easily spelled out by translating them into their conceptual definitions. Thus, *p(a1)* for *C* means that, in a social group where members know on average s_1 properties of k_1 potential properties for concept *C*, the probability that a given member will find confirmatory evidence for her current conceptualization *C*, where this information is being provided by another group member whose current conceptualization is also *C*, equals 0.6. Similarly, *p(a2)* for *C* means that, in a social group where members know on average s_1 properties of k_1 potential properties for concept *C*, and where there is an alternative *Cn* conceptualization with k_2 potential properties that partially overlaps with *C* by a given *u* number of properties, the probability that a given member will find confirmatory evidence for her current conceptualization *C*, where this information is being provided by another group member whose current conceptualization is not *C* but *Cn* instead, equals 0.3. An analogous translation can be made for concept *Cn*.

CONCEPTUAL DESCRIPTION OF THE MODEL

It seems obvious that concepts must be learned. Learning those concepts is part of what makes people members of a given social group. Interestingly, because people are exposed to different experiences, it is likely that they will end up with somewhat different conceptualizations (i.e., there will be intersubjective variability). Furthermore, in contrast to learning a fact of the matter (e.g., that dogs bark), learning about what we call diffuse concepts (as discussed above) arguably requires learning from others whatever is associated with the concept in question. Thus, our Agent-based Model (ABM) always starts a simulation run with agents needing to learn the available concepts. In the agents' environment, there are only two concepts (*C* and *Cn*) and a number of potential properties for those concepts (the same properties are potentially associated with both concepts). These two concepts and potential properties represent that concepts are learnable for all agents (i.e., all agents have access to the concepts' potential properties), and provide only a minimal structure so that conceptual structure and agents' agreement may emerge from the agents' interaction history, and not from externally provided information. With regard to those ideas, our ABM may be considered of the bounded confidence type of model (Castellano et al. 2009), focused on the development of diffuse concepts and without imposing a communicational topology among agents. Also, given that CAT states that meaning is inferred between agents, our ABM is similar to the discrimination model (Smith 2001), but much simpler. In Smith (2001), agents use reinforcement learning and keep in mind large discrimination trees, whereas in our ABM only property distributions are kept. Studies have empirically proved that individuals are able to hold in their minds and use frequency distributions (Kane and Woehr 2006; Steiner et al. 1993; Woehr and Miller 1997), which lends face validity to our ABM.

To learn, an Observer (*O*) agent actively queries an Actor (*A*) agent by asking it whether property *i* belongs or not to concept *C* (or to concept *Cn*) in *A*'s mind. To create the query, *O* randomly chooses either concept *C* or *Cn*, and then randomly chooses one property among one of a number of potential properties in its environment. (For ease of explanation, we will discuss learning for concept *C*, but exactly the same applies to learning concept *Cn*.) After receiving the query (e.g., is *i* a property of *C*?), *A* consults its own conceptual content for the concept in the query and responds. If its concept is empty (as it may occur at the beginning of a run), *A* chooses a property from the environment, adds it to its concept, and answers the query. If the query is answered positively (i.e., yes, property *i* belongs to *C*), *O* increases the evidential value of property *i* for the concept in question (i.e., *C*) in *O*'s mind. If the query is answered negatively, *O* decreases the evidential value of property *i* for concept *C*. In case the query is answered positively and that property *i* is already part of the alternative concept (i.e., *Cn*), *O* increases *i*'s evidential value only in half (because it is evidence for two different concepts). The same happens when *O* decreases the evidential value.

If left unbound, the simple learning mechanism outlined above would probably make all agents eventually learn all the potential properties for the two alternative concepts. Agents would end up with two concepts *C* and *Cn* with identical content (i.e., there would not be intersubjective variability). An issue that becomes critical here, then, and that has received little attention in the literature, is whether people stop learning concepts at some point and how do they decide when to stop. If they never stopped, would that lead to everyone having the same conceptual content? In contrast to experimental settings, where people learning concepts are subject to an external standard that will stop learning (e.g., because they achieved asymptotic performance on some learning criterion), in natural settings people must decide for themselves when to stop learning. In our ABM, Observer agents that are learning and that receive positive answers to their queries (as discussed above) decrease the probability of continuing learning, while agents that receive negative answers to their queries, increase the probability of continuing learning. (Increased learning on the face of the unexpected, is a mechanism present in several learning theories, and traceable at least to the Rescorla-Wagner (1972) model of Pavlovian conditioning.) Consequently, the more agents successfully learn, the more probable it becomes that they will use their concepts for communication instead of attempting to learn. When using a concept for communicating, an *O* agent randomly chooses between *C* and *Cn*, and waits for an *A* agent to produce a property *i* (note that this is the idealized conversational structure we discussed above). Imagine now that *O* chooses concept *C* and that property *i* produced by *A* is in fact part of that concept's conceptual content for *O*. In that case, *O* would infer agreement, either true or illusory. Furthermore, in case of agreement being found, *O* increases that property's evidential value for the corresponding concept.

Note that the ABM rules allow agents to stop learning when concepts permit sufficient agreement for communicating, implying that it is not necessary to continue indefinitely learning a concept, and thus allowing that intersubjective variability occurs. Furthermore, because agents in our ABM learn from other agents in their community, the amount of learning that is necessary depends on variables of the agent group, much as may occur in real social groups (as will be discussed later).

THE ABM'S IMPLEMENTATION AND EXPERIMENT DESCRIPTION

To model the conceptual description, we developed the simplest possible ABM abiding by the *KISS* principle (Keep it simple stupid, Axelrod 1997). In the ABM, akin to Figure 1, there are two concepts *C* and *Cn* and *P* properties that may be part of both concepts. Those properties are represented by numbers from 0 to *P-1*, similarly as depicted in Figure 1. Through the interaction of *N* agents, agents will form in their minds the conceptual structure for *C* and *Cn*, by assigning from the universe of the *P* properties, some to *C* and some to *Cn*. Given that some properties may be assigned by agents to both *C* and *Cn*, there might exist an overlap of properties between *C* and *Cn*. The assignment of properties to concepts is modeled by *P* evidential variables $EC_i \geq 0$ and $ECn_i \geq 0$, $i = 0$ to *P-1*, that exist in each agent's mind. A variable EC_i bigger than zero means that the agent has evidence that property *i* is associated with *C* in its mind. The same happens with ECn_i for the properties that belong to concept *Cn* in each agent´s mind. The interactions between two agents can be of two types: learning and agreement. The learning interaction models the way agents experience the concepts and learn a concept by assigning properties to concepts and asking for the opinion of other agents regarding that selection. The agreement interaction models how agents communicate among them according to CAT and change their conceptual content depending on whether concepts furnish agreement for communication. The interaction type is probabilistically selected by each agent by means of a learning probability *L* in the [0,1] interval, which each agent has and will change during the course of a simulation run. At the beginning of a run, given that agents need to learn the concepts, *L* is set to 1. During a run, that initial value for *L* will increase or decrease by an amount equal to *Delta_L,* which can be set at a beginning of a run for all agents. In the ABM, agents may represent an Observer (*O*) or an Actor (*A*). The following is the description of a simulation step:

1. From the *N* agents, randomly select without replacement one agent as Observer (*O*). Then *O* randomly selects an agent from the rest of the *N - 1* agents as Actor (*A*).
2. *O* probabilistically decides whether to interact with *A* in learning mode (according to its learning probability (*L*) that *O* has in its mind). Thus, *O* can also decide to interact in agreement mode with probability equal to *1 - L*.
3. Learning interaction:
   a. If in step 2 *O* decides to interact with *A* in learning mode, then *O* randomly selects one of the two concepts (*C* or *Cn*), and one property *i* from the *P* possible properties and presents that tuple to *A*.
   b. If the presented concept in *A*'s mind does not have associated to it a property (i.e. $EC_i = 0$ or $ECn_i = 0$, $\forall i$, $i = 0$ to *P-1*), then *A* randomly selects one property *i* from the *P* possible properties and assigns it to the chosen concept. That means that *A* will increase the corresponding EC_i or ECn_i. That increment may be 1 if property *i* exists in *A*'s mind only for one of the concepts, or 0.5 if it exists for both concepts. Then, *A* verifies whether that tuple exist in its mind and communicates that to *O*. That means that *A* will check whether the variable EC_i for concept *C* or ECn_i for concept *Cn,* for property *i*, is bigger than zero.
   c. If the reply from *A* is affirmative, then *O* increases EC_i for concept *C* or ECn_i for concept *Cn*. That increment may be 1 if property *i* exists in *O*'s mind only for one of the concepts, or 0.5 if it exists for both concepts. *O* also decrements *L* by an amount equal to *Delta_L*. This means that since the learning activity was successful, the *O* will increase its probability of acting in agreement mode, i.e. given that *O* better learned a concept, it will increase the probability of using it for communicating.
   d. Contrarily, if *A*´s reply is negative, then *O* decreases EC_i or ECn_i in the same form already explained. Given that in this case, the learning activity was not successful, the *O* will increase *L* by an amount equal to *Delta_L*, which means that it is now more important to *O* to continue learning the concepts.
4. Agreement interaction:
   a. If in step 2 *O* decides to interact with *A* in agreement mode (with probability equal to *1 - L*), then *O* randomly selects one of the two concepts (*C* or *Cn*) and waits for *A* to produce a property.
   b. *A* randomly selects the concept *C* or *Cn* and randomly chooses one property *i* for the selected concept. If the selected concept in *A*'s mind does not have associated to it a property (i.e. $EC_i = 0$ or $ECn_i = 0$, $\forall i$, $i = 0$ to *P-1*), then *A* randomly selects one property *i* from the *P* possible properties and assigns it to the chosen concept, which means that *A* increases the corresponding EC_i or ECn_i by 1 or 0.5 according to the same rule used by *A* in 3b. Next *A* presents property *i* to *O*.
   c. *O* gets *A*'s property *i* and verifies whether that property is part of its version of the concept selected by *O* in 4a. That means that *O* will see if EC_i or ECn_i is bigger than zero in its mind. If that is the case, *O* will increase EC_i or ECn_i by 1 or 0.5, according to the same rule used by *O*

in 3c. In terms of CAT, that means that given that *A* furnished confirmatory evidence about concept *C* or *Cn*, the corresponding property will be useful for communicating in future interactions.

d. If property *i* is not contained in the selected concept, then *O* does nothing. According to CAT, because no agreement was found, *O* does not strengthen the association of property *i* with its concept.

5. Repeat steps 1 through 4 until all agents have been *O*'s.

Though this may not be apparent, the most important difference between learning and agreement interactions is that only in learning mode, and only when *A*´s reply to *O*´s query is affirmative, *O* agents are able to associate new properties with concepts throughout a simulation run. Note, however, this is not true at the very beginning of a run, where *A* agents are able to relate new properties to concepts in both interaction modes, and without needing a reply from the *O* agents. This is necessary to kickstart a run, given that *A* agents initially lack conceptual properties.

The ABM's outputs used in this paper to analyze the model are the following:

1. The total number of properties for concept *C* in the population of agents (k_1) at the end of a simulation run. That figure is calculated according to CAT. After a run is finished, the ABM counts all the EC_i that are bigger than zero among all the agents. The same for concept *Cn* (k_2), but counting the ECn_i that are bigger than zero.
2. The average number of property types coherent with concept *C* in agents' minds (s_1). Each agent counts how many EC_i are bigger than zero in its mind and reports that number to the ABM. Then the ABM averages those numbers over all agents. The same is done for concept *Cn* (s_2).
3. The number of property types that are consistent with *C* and with *Cn* (i.e., *u*, the cardinality of the $C \cap Cn$ set, see Figure 1).The ABM counts the number of EC_i and ECn_i that are simultaneously bigger than zero in any agent mind.

We set up the initial learning probability at 1.0 in all experiments, which means that agents begin by learning concepts. This must be so, given that at the beginning of a run, agents do not have any conceptual information in their minds and thus need to learn concepts. Nevertheless, we also used very low initial learning probabilities such as 0.001, and the results that we present here remained the same, which means that results are robust to such parameter. The manipulated input parameters correspond to *N* (number of agents) and the total number of possible properties (*P*), which were set at 10, 50 and 90; and the amount by which the learning probability is increased or decreased in *O*s' minds (*Delta_L*), which was set at 0.05 and 0.2. We performed a $3^2 2^1$ full factorial experiment, comprising 18 different experimental conditions and each condition was replicated 10 times. We chose that design given that we suspected non-linearity in the outputs of the ABM. Values for *N* and *P* were chosen to represent small, intermediate and large groups of agents and concepts that could also have a small, intermediate and big number of potential properties, which in this study represent the independent structural elements of the communication system. In general, the more potential properties the system has, the more complex it will be (c.f. Freeberg et al. 2012). Regarding *Delta_L*, we selected a small value for representing a long learning period for agents and a rather high value for modeling a rather short learning period. Finally, the termination condition of a run is defined as the time when the ABM reaches a steady state condition. In that condition, the relevant outputs of the ABM (k_1, k_2, s_1, s_2, *u*) remain unchanged. To automatically detect that condition and stop a run, the ABM computes the standard deviation of those figures over a sliding window of 3,000 steps and if all the standard deviations fall below 0.005, it finishes the run.

RESULTS

In the next analyses, we present the results for concept *C*, given that the results for *Cn* are analogous. Moreover, remember that we are mainly interested in the *p(a1)* and *p(a2)* values and that according to (1) and (2), those probabilities can be calculated using k_1, k_2, s_1, s_2 and *u*. Thus, most part of the analyses use those probabilities. Figures 2 and 3 present graphs of *p(a1)* and *p(a2)* for the 18 experimental conditions. We should note that we performed an ANOVA for the full factorial model and all the components of the model for both *p(a1)* and *p(a2)* are statistically significant (p-values ≤ 0.02), except for the *N* x *Delta_L* interaction (p-val = 0.325) and the *N* x *P* x *Delta_L* interaction (p-val = 0.225) for *p(a2)*. Although most parts of the model are statistically significant, in this paper we will focus on analyzing main effects and some of the double interactions.

Figure 2 indicates that the smaller the size of the group (small *N*), the higher *p(a1)* is. Thus, we can say that small groups will tend to reach a higher true consensus on the meaning of concepts then larger groups. Additionally, the graph suggests that this difference is more noticeable for a bigger *Delta_L*. *Delta_L* regulates how fast the group focuses on agreement interactions and finishes the conceptual learning process, where a smaller *Delta_L* implies a longer learning period.

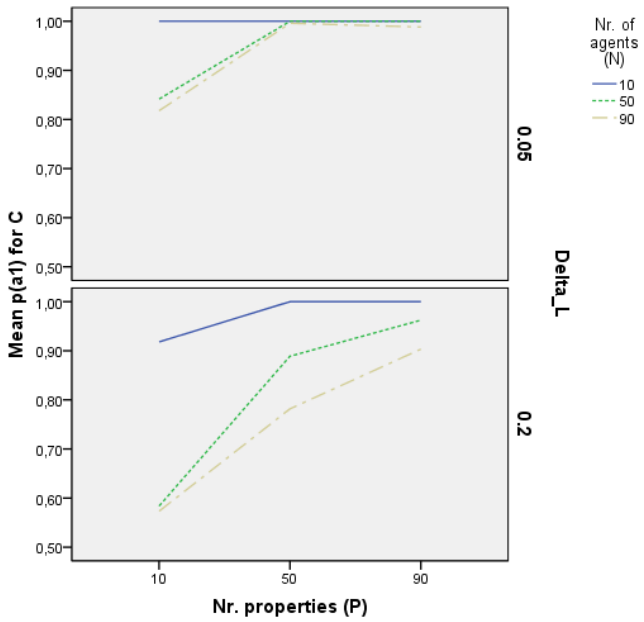

Figure 2: Average $p(a1)$ Values for the 18 Experimental Conditions (avg. over 10 replications for each condition)

Thus, a small *Delta_L* allows agents a longer learning process, asymptotically increasing the number of properties that are assigned to concept *C* (k_1) from the total number of possible properties (*P*). The same happens with the size of the average number of property types coherent with concept *C* in agents' minds (s_1). Therefore, the concept becomes more homogeneous across agents' minds, even if the number of agents increases. Note that since $p(a1) = s_1/k_1$, that explanation is clearly backed up by CAT. The contrary happens with a bigger *Delta_L*. The learning process finishes faster, and thus agents are not able to incorporate many properties in their minds. If the number of agents increases, that situation fosters heterogeneous versions of the concepts in agents´ minds. Finally, note that the bigger the universe of properties to describe a concept (*P*), the higher $p(a1)$. This happens because the greater the number of available properties, the more difficult it is for agents to reach consensus on the set of properties that characterize a concept, and thus the learning period is longer. Therefore, agents are able to describe the concept with more properties, which asymptotically increases k_1 , s_1 and $p(a1)$. Also, a bigger group (larger *N*) tends to incorporate more properties into concepts (larger k_1), given that more agents interact and each of them can associate different properties to concepts. It is important to mention that, as the ANOVA's significant interactions terms suggest, the effects of the number of agents, *Delta_L* and number of properties on $p(a1)$ interact. For example, more properties slow down the learning process, but that delay is also affected by the *Delta_L*. Also, with a relatively bigger number of agents, *Delta_L* influences the duration of the learning process more significantly than with fewer agents, and correspondingly $p(a1)$, as already explained. The increase in k_1 due to the already explained factors is analogous to the findings of Lehmann et al. (2011) for cultural traits of a society, where the number of traits increases with population size.

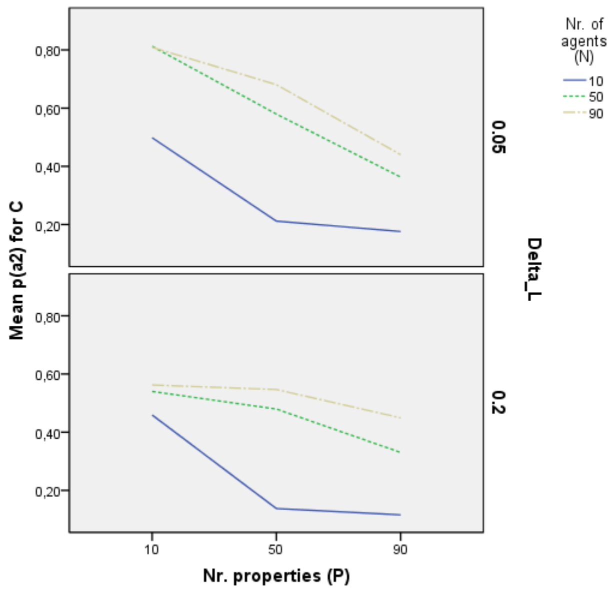

Figure 3: Average $p(a2)$ Values for the 18 Experimental Conditions (avg. over 10 replications for each condition)

In the case of $p(a2)$, Figure 3 shows that the smaller the group, the lower $p(a2)$ is. Given that few agents will have less chance of learning many properties for a concept, then the number of properties that might be simultaneously learned for both concepts will decrease, making u (the number of properties that belong to both concepts) smaller. Given that according to CAT $p(a2) = p(a1)\, u/k_2$, the smaller u implies a lower $p(a2)$. Figure 4 presents a graph that indeed shows that as the number of agents decreases, u becomes smaller. However that graph also indicates that for a relatively big number of agents ($N = 90$), u does not monotonically decrease as the number of properties increase. Given a small number of properties, necessarily only a few can belong to both concepts, even if many agents interact, i.e. there is a natural limit on the maximum number of properties that can belong to both concepts. In that case note from Figure 4 that u ≈ 10 ≈ *P*. Now, if the number of properties grows, then a relatively big number of agents can associate more properties with both concepts, and thus u can increase. However, if the number of properties continues increasing, then there are so many available properties for both concepts, that even a large number of agents cannot incorporate all of them in each concept, which makes u decrease. Alternatively, we can say that there is a compromise between the number of available properties and u when there is a large number of agents. Few properties foster a low level of diversity in conceptual learning and thus it is easy for a large number of agents to associate most of those properties with both concepts. On the contrary, if many available properties exist, that promotes a high level of diversity, thus the probability that many of the same properties are included in both concepts decreases, if the ratio of number of properties to number of agents is too high.

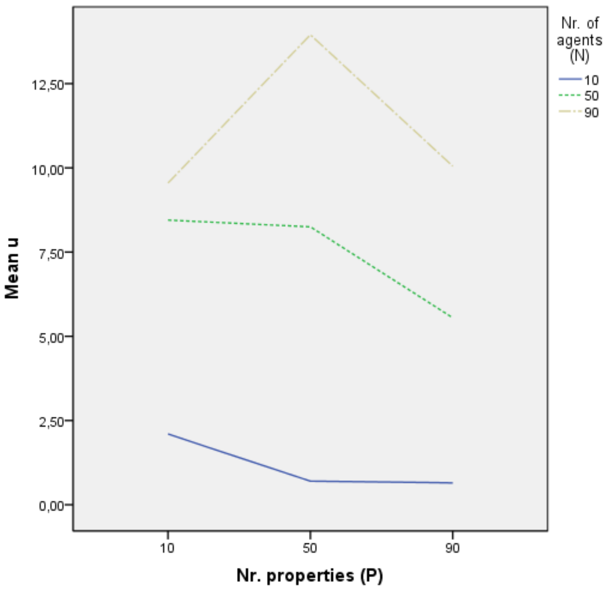

Figure 4: Average u Values for Different P and N (avg. over 10 replications for each condition)

DISCUSSION/CONCLUSIONS

If we jointly analyze the effect of the factors on *p(a1)* and *p(a2*), we can draw interesting additional conclusions. Our results are broadly consistent with Dunbar's social complexity hypothesis (Dunbar 1993; Freeberg et al. 2012), but add several interesting nuances. Recall that the social complexity hypothesis states that there is a direct relation between the complexity of social systems and the complexity of the communicative systems that regulates their interactions (i.e., the number of independent structural elements). At a very broad level of analysis, we found that in our simulations, the greater the number of agents, the greater the number of properties that are incorporated into their concepts. This is precisely what the social complexity hypothesis holds.

Now, to the nuances. A first nuance is that our simulations predict that large groups will produce complex communication systems but at the expense of introducing uncertainties in communication (i.e., less true agreement and more illusory agreement relative to small groups). Small groups in our simulations tend to develop quite simple concepts (i.e., with a small k_l and s_l). On the up side, these simple concepts produce rather high *p(a1)* and low *p(a2)*, meaning that small groups create a conceptual structure that fosters low uncertainties in communication. However, on the down side, this occurs because small groups are fast to close concepts, as soon as those concepts allow agreement. Thus, their concepts reflect more the structure of their common history of interactions than the concept's initial structure (recall that the initial structure stipulates that any property could be associated with any concept). In stark contrast, large groups develop rich concepts (i.e., large k_l and s_l) that depend less on the group's history of interactions, but at the expense, as already stated, of relatively lower *p(a1)* and higher *p(a2)*, while still preserving that *p(a1)* > *p(a2)* (which is a requisite for communication).

A second nuance is that our simulations predict that in the real world, the *Delta_L* parameter should have an important influence on the conceptual structure that groups will develop. In the ABM results, *Delta_L* interacts with the number of agents (*N*) and number of properties (*P*) for *p(a1)*. Thus, those three variables dictate the size of the set of properties that describe a concept (k_l) and the average number of property types coherent with a concept in agents' minds (s_l). Such a combination of the corresponding real world parameters, will affect the rate at which people learn concepts and when individuals think that they should stop learning. That will in turn influence the richness of the conceptual structure that people may acquire through time. Though the number of properties and the size of the social group are both variables in the social complexity hypothesis, a new idea that our ABM offers is that there is a difference between leaning concepts versus using concepts for communication, and that the complexity of a communication system may depend also on how soon people stop learning and start using concepts (i.e., the *Delta_L* parameter). It is possible that in real social systems many psychological and social variables could influence the *Delta_L* parameter, and thus affect the complexity of concepts used in that group. We believe that the influence of the *Delta_L* parameter in our simulations suggests that for the development of real communication systems, it is necessary that concepts remain open to learning for a prolonged period. Although all the above-discussed conclusions seem intuitively plausible, notice that the results show that the effects of the factors are highly non-linear, with many interactions among the factors. Also, as Figures 3 and 4 suggest, these interactions even change the direction of the curvature of the effects, which is an interesting issue to be investigated. In particular, as already discussed, Figure 4 shows that for large groups, u increases with the number of properties, but then decreases, effect that we think is far from being intuitive.

Now we turn to offer a real world example that could follow a similar dynamics as discussed above. A many times replicated finding is that children from lower Socioeconomic Status (SES) increase their vocabularies at slower rates than children from higher SES, and probably end up with smaller vocabularies overall (e.g., Morrisset et al. 1990). If we take this small vocabulary size to be roughly analogous to a small number of properties in concepts in our simulations, it seems obvious that this phenomenon occurs because, just as in our simulations, the process of learning a communication system will stop when concepts being learned become useful for communication. It's again obvious that this is controlled by characteristics of the environment of the group where learning takes place. If the environment where a group exists has a small number of potential properties to describe concepts (i.e. a small *P*), then learning will stop soon and no further properties will become associated with the concept, because there is nothing more to learn. However, our simulations suggest insights further from the obvious, which may even be empirically tested. All other things being equal, SES groups that are larger or better connected should have more complex communications systems (i.e., larger vocabularies, richer concepts). Up to a certain limit, if a social group has more intersubjective variability in conceptual content, then its members should have richer concepts. If children from low SES interact early in life with large and heterogeneous groups, they should develop larger vocabularies and richer concepts. If the *Delta_L* parameter could be somehow manipulated, then people would remain in a learning phase for sufficient time to allow their vocabularies and concepts to be influenced by increasingly large and diverse groups, making their concepts correspondingly richer. We acknowledge that in this example we are equating words (the vocabularies) with conceptual properties, and that this may be questioned. Note, however, that a clear-cut separation between properties and concepts is achieved only at the level of concrete nouns (e.g., it seems perfectly valid to say that *wags its tail* is a perceptual property of the concept *dog*). In contrast, abstract words (which we have labeled here, *diffuse concepts*) have other words and concepts as properties (Recchia and Jones 2012). It is true that the properties of abstract concepts are probably semantic properties rather than plain properties. However, we believe they can be treated the same when modeling communication.

Finally, note that all these conclusions are tentative, pending further validation of the ABM. We have already validated with empirical data CAT regarding the validity of equations (1) and (2), i.e. the calculation of the probability of true and illusory agreement. Thus, given that the ABM is based on CAT and other generally accepted theory, which lend face validity to the model, we believe that the ABM could be plausible enough to be used to conduct "thought experiments" (Axelrod 1997). Hence, one could use this ABM to gain insights into the phenomenon and develop hypotheses that could be then tested through experiments with human subjects. All that is part of our future work with the model, which will also include ABM´s experiments with different types of communication topologies among agents, to further delve into the social complexity hypothesis of communication systems (Dunbar 1993; Freeberg et al. 2012).

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