The Roundtable: An Agent-Based Model of Conversation Dynamics

Massimo Mastrangeli[1], **Martin Schmidt**[2], **and Lucas Lacasa**[3]
[1]MTM Department, Katholieke Universiteit Leuven, Leuven, Belgium
[2]Department of Economics, University of Maryland, College Park, USA
[3]IFISC, Instituto de Física Interdisciplinar y Sistemas Complejos (CSIC-UIB), Mallorca, Spain

---

Abstract. What mechanisms drive the group size evolution of social conversations? How does schisming take place in dynamically-changing conversations? Are there any universal driving mechanisms taking place? In this work we address such questions by means of an agent-based model of conversation dynamics. The proposed model develops from simple yet realistic assumptions derived from experimental evidence, it abstracts from conversation content and semantics while including topological and simple psychological information, and it is driven by stochastic dynamics. It describes the turn-taking dynamics of an abstract N-body conversation. We find that a single mechanism, *i.e.* the dynamics of individual fitness thresholds that characterize the happiness level of each participant, enables the onset of complex collective phenomena such as the self-organized schisming phenomenon. Potential generalizations of the model - including individual traits and preferences, memory effects and more complex conversational topologies - may find useful applications also in other fields of research, where dynamically-interacting and networked agents play a fundamental role.

Keywords: *ABM, social simulation, conversational analysis, turn-taking dynamics, schism*

Disclaimer: *all (pseudo-)codes as well as NetLogo implementations utilized in and derived from this work are freely available under request.*

Introduction

The glorious Santa Fe Institute's Complex Systems Summer School 2009 took place mainly in St. John's College - in the high end of Santa Fe (NM, USA). Breakfast, lunch and dinner were taken during fixed time slots in a fixed location, the cafeteria. Nearly all available tables were arranged so that groups of up to 20 people could comfortably sit in quasi-circular ensembles, consume their meals together and enter into inspiring conversation. An external observer could incidentally discern that table conversations were not stable. Not only did table topics change in space and time: interestingly, not all participants seated around the same, specific table took part at all times in a table-wide conversation. Usually, participants took part in conversations that involved only a subset of the people seated around that table. As a result, each table had multiple, separate sub-conversations going on at the same time. Moreover, people taking part in one of these parallel chats usually did not remain involved in the same sub-conversation indefinitely, but tended to leave their original sub-conversation and join another, possibly neighboring one going on at their same table.

Was this set of behaviors accidental, or was there, on the contrary, any general *underlying mechanism* driving the group size evolution of conversations? Such questions have been addressed in social sciences from several perspectives. The general issue of pointing out the sociological factors that determine the group size of a conversation dates back to the seminal work of Simmel [1]. The phenomenon that occurs when a single turn-taking conversation splits up into two or more sub-conversations, referred as *schism*, was firstly investigated by Sacks and collaborators [2], and further developed by several authors [3-8]. Related studies addressed the effect of different social-based features in the schisming mechanism, ranging from schisming-induced turns [3] to multi-focused gathering [4] and to co-occurrence of turn-taking systems [2,5]; specific behaviors were documented by concrete experiments, such as video tape recordings [2,6], everyday experience [4] or hypothesizing and reasoning methodology [1]. Interestingly, significantly-less work addressed the analysis of abstract, context-free conversations, and the specific role that purely stochastic dynamics may play in the process of schisming. These problems were probably difficult to tackle in early times since all empiric evidence were, by definition, context-based conversations. However in recent years, along with the large improvement of computer performance, it has been possible to circumvent this latter restriction thanks to the framework of social simulations [17]. This was developed to improve the understanding and/or to evaluate strategies, explanatory and predictive schemes of the behavior of social systems whenever – for *e.g.* practical or ethical reasons - it was impossible to realize direct observations. The well-established agent-based model paradigm [9] has proven to be a fruitful framework to simulate social-based collective phenomena [17]. Now, while several authors approached the simulation of multi-party interaction in the last years, the large majority of these works were pursued in the context of machine learning, addressing specific challenges in artificial intellingence such as *e.g.* human-robot interaction [10] or pattern recoginition [11]. Indeed, automated analysis of multi-party interaction was applied in different scenarios, such as *e.g.* co-present meetings in smart meeting rooms for archival and assistive purposes [12,13], or remote interaction [14]. Little work addressed fundamental questions of self-organized conversation dynamics.

In this paper we propose to describe the emergence of conversational schisming as a complex collective phenomenon [15, 16, 18]. Based on simple yet realistic rules, we present an agent-based model (ABM) that simulates, driven by stochastic dynamics, the time-evolving size of a conversation groups. We analyze how schisming develops in such setting, and we describe the process of multi-party generation. Since our model is deliberately abstract and context-free, our conclusions are general and do not restrict to a particular class of turn-taking conversations. Furthermore, proposed generalizations of our model may find useful applications in other research areas, as well.

The rest of the paper is organized as follows: in Section 2 we present the baseline conversational model, defining the basic agent rules. In Section 3 we implement such model and provide the results of several simulation runs; particularly, we distinguish between transient dynamics, like real-life conversations, from stationary dynamics, which is the (probably unrealistic) asymptotic limit of the dynamics which, nonetheless, can in some cases be solved analytically in a mean-field approximation. We also provide empirical evidence that reasonably matches our numerical studies. Finally, in Section 4 we provide a summary of conclusions, as well as a discussion on the possible model generalizations and further applications of the work.

The baseline model: assumptions

We defined our *baseline agent-based conversational model* by instantiating a set of simplifying yet realistic assumptions:

0. *Homogeneous initial conditions.* At the beginning, all people participate in a unique conversation and are in the same state. The conversation starts with a random participant entitled to speak – she will be called *the speaker* - while all other participants are *listeners.* While other initial configurations can of course be imposed, the dynamics tends towards attractors whose basins of attraction are global (as we shall later see): every initial condition will thus tend to the same steady state. Hence, without lack of generality, we choose a homogeneous initial condition for simplicity.

1. *Roundtable*. The participants are arranged around an ideal roundtable (*i.e.* a one-dimensional torus with periodic boundary conditions): in principle each participant can speak with any other participant, but she is in direct (*i.e.* spatial) contact only with her two nearest neighbors - which define her own topological neighborhood. While this time-invariant conversational geometry could seem too simplistic *a priori*, it is worth noting that realistic, spatially-embedded conversations tend to cluster in a circular-like geometry: this is reminiscent of what we will define below as the "conversational principle of least effort".

2. *Turn-taking dynamics*. In a given conversation, only one person (the speaker) speaks at any given time before another participant (a listener) of the same subgroup is entitled to speak. Note that within a single group, different separated sub-conversations can nucleate: in this case, we assume for simplicity that the speakers of all sub-groups are appointed concurrently and simultaneously (this synchronous updating rule can be relaxed if needed). Note that this rule introduces a turn-taking dynamics: at every turn, each conversational group has a speaker different from that of the previous turn.

3. *Abstraction from conversational content*. We model the succession of speakers within any given conversation group as a stochastic process. In principle, it is possible to use any kind of speaker-dependent or history-dependent probability distribution to establish the choice of the new speaker. However, in this work we wonder whether complex patterns in the schisming dynamics can still develop under the conditions we are assuming, without the need for additional and detailed individual information. This approach is reminiscent of the *complexity paradigm* [15, 17, 18], which we deliberately adopt here. Note that this approach is also coherent with content abstraction: any kind of emergent conversation pattern will be consequence of the cooperative behavior that takes place when

participants interact, rather than an eventually concrete mixture of ill-defined mechanisms. The probability distributions adopted in the baseline model are uniform, *i.e.* speaker- and history-independent.

4. *Joining/leaving force balance*. Participants in a specific conversation remain in the conversation as long as they have the opportunity to speak regularly, while they wish to leave the conversation as soon as they feel excluded from or unexcited by the conversation, *e.g.* because they do not have the opportunity to speak or to be somehow actively involved in it up to their preferred degree. We model this lively behavior by assigning a *happiness status* to each participant of the conversation. The baseline scenario has all participants initially involved in the same table-wide conversation and assigned with the maximum level of the happiness scale, which is set equal to that of anyone else – *i.e.* we optimistically assume a person is happy to take part in a conversation that is about to start; again, different initial conditions would evolve towards the same stationary state, as we will see. The happiness level is then subjected to dynamic change. It is decreased by *one unit* for every conversation turn during which the participant is not a speaker, while it is reset back to the initial level when the person gets a new opportunity to speak. As soon as the happiness level drops to the minimum tolerated level (set to zero in the baseline model), the participant becomes *latent*, *i.e.* she feels excluded enough to watch out around her for opportunities to enter another or new conversation. Our agents can thus be considered as finite-states automata with a set (ideally, a continuum) of states between the fully conversation-integrated state (*i.e.* the speaker - state of maximal happiness) and the fully-excluded state (*i.e.* the latent - state of minimal happiness). Corollaries: a) a speaker is always fully happy; b) a latent is necessarily a listener.

5. *Neighborhood-based schism dynamics*. When a participant is in the latent state, she will look to her topological neighbors to be eventually engaged in a new conversation – schism then takes place. She will first check whether at least one of the neighbors is in turn latent: if this is the case, she will start a new conversation with her/them. This nucleation mechanism is the responsible for the onset of schisming in our model. Otherwise, she will anyway join the ongoing conversation of either of her neighbors[1]. In these cases, her happiness level will recover and will be reset to its maximum level. If none of these options are possible, the agent remains latent, waiting for someone to talk to him (and to re-enter in his previous conversation) or waiting for someone to go latent or for a different conversation to take place. The use of only local resources to escape from a stagnant conversation is what we define as the *conversational principle of least effort*.

To verify the extent to which our simple assumptions capture realistic features of real-life conversations, we implemented them and inspected the emergent behavior they generate in an agent-based model. The simulative investigations were complemented with analytical methods and insights where possible.

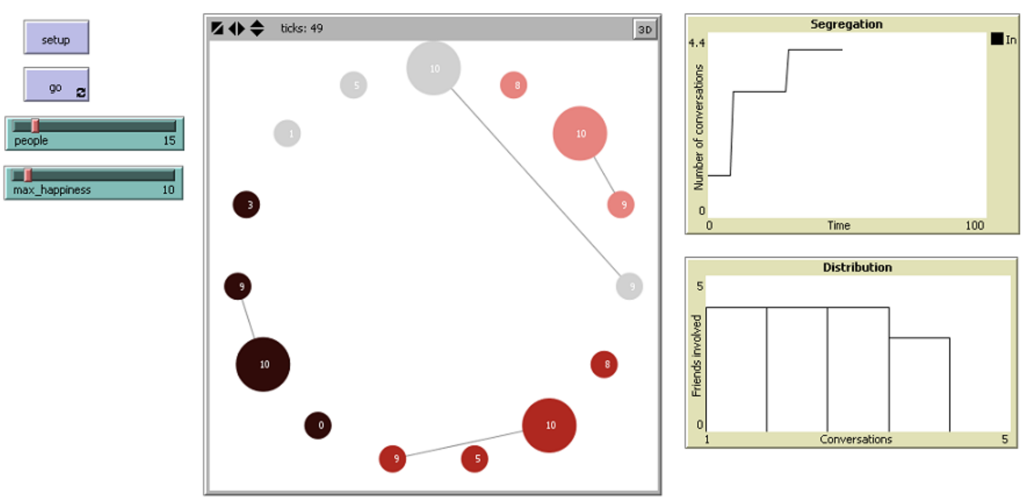
The baseline model: analytical and numerical results

As described in the previous section, in the baseline model every participant in the original conversation has the same initial happiness level (set to the maximum value), and makes use of a uniform probability distribution for the choice of a new speaker among the listeners. One can think of this configuration as a situation where a homogenous group of people is engaged in leisurely chat without selection biases due to accidental geometry, common interests, hierarchies or previous discourse patterns.

We implemented the baseline model in NetLogo (NetLogo is freely available at: http://ccl.northwestern.edu/netlogo/). In Figure 1 we show an example of the customized graphical user interface.

Running the ABM with the homogeneous initial condition, it is found that the initial table-wide conversation group splits over time into several sub-convsersations of smaller group size. This is akin to a spatial symmetry-breaking phenomenon: the initial, spatially-homogeneous system (*i.e.* lacking boundaries) evolves into one with spatially-defined boundaries. This splitting process continues - despite temporary increases of the sizes of conversation groups – until the conversation groups cannot split any further, that is, until each sub-conversation reaches the absorbing state where it involves only two agents (as long as there are more than 2 people in a conversation, there exists always a non-null probability that one participant will not speak before her happiness level decreases to the minimum value, driving her to leave the conversation; this is true independent of the number of participants in the conversation and of their maximum happiness level). Note at this point that, in the case of an *even* initial number of agents, the asymptotic configuration presents N/2 sub-conversations of two agents, while if the initial number of agents is *odd*, it is formed by N/2-1 sub-conversations of 2 agents and a single sub-conversation of three agents. Equivalently said, the optimal though only asymptotic number of parties in a conversation, according to the baseline model, is predicted to be essentially 2.

Figure 1: Customized NetLogo graphical user interface for the baseline model. Different colors in the roundtable agents denote different conversations.



The characteristic time until reaching this steady state (that is, the characteristic amount of turn-taking time steps) typically depends on two factors, namely 1) the number of agents, and 2) the maximum happiness level. For instance, if we fix the maximum happiness level to infinite, the steady state will never be reached, while if we fix it to 1, it will be reached very soon. Numerical simulations suggest that this characteristic time scales exponentially with the overall maximum happiness level (see figure 2), and linearly with the number of agents (as a matter of fact, maximum happiness level and number of agents are two related factors from the computational point of view, since their basic effect – decrease the probability of a single agent to be entitled as speaker – is similar). Also, as we shall see, this rather trivial asymptotic state is hardly reached in real-life conversations, that typically develop in shorter timescales than the stationary characteristic time.

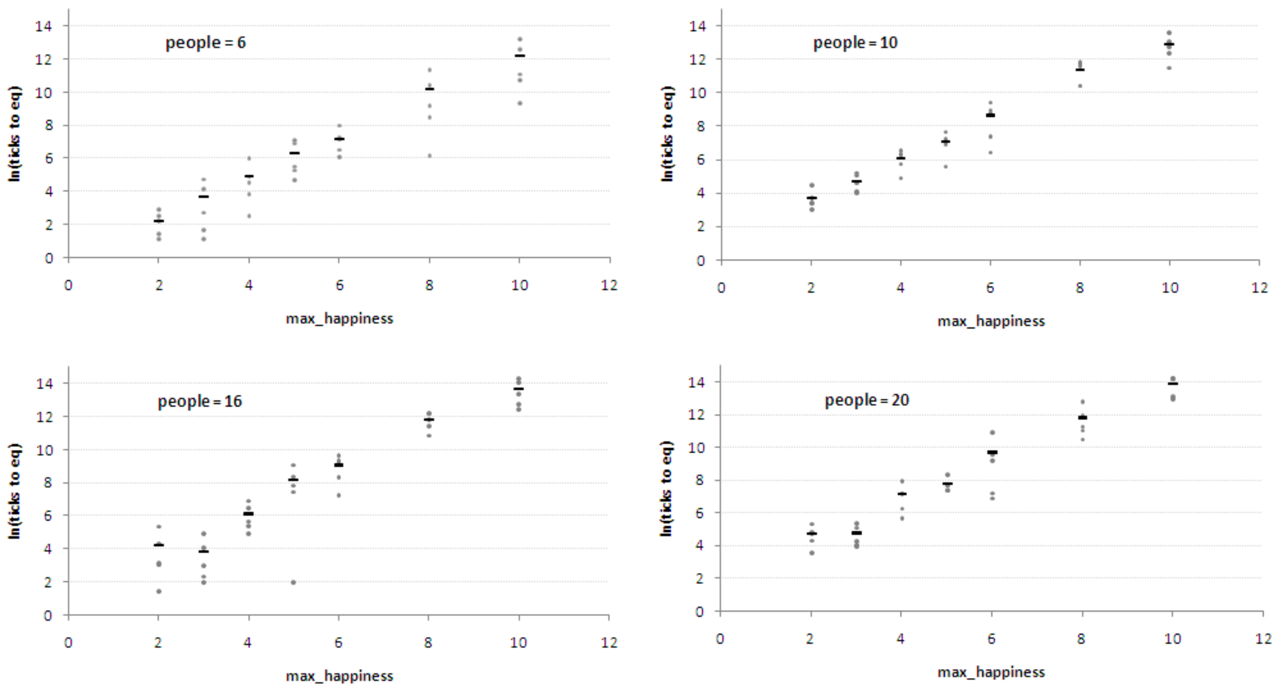


Figure 2: Semi-log plots of the characteristic time needed to reach the steady state, for different settings of the maximum happiness level (data averaged over 5 simulation runs). The straight line denotes exponential scaling.

Mean-field approach

In a mean field treatment of the baseline model, we will assume that the probability p_i of a participant in a conversation to be entitled to speak by the present speaker at time t is: 1) independent of previous conversation history, and 2) constant in time. In general, $p_i = p_i(N,i)$ where N is the number of participants, and the specific dependence of p_i on each participant characterize individuality, both intrinsic (*e.g.* psychological factors) or extrinsic (*e.g.* conversation geometry). Let $F_i(t)$ be the happiness level of participant i at time t; for what said before, $F_i(t)$ is semipositive definite.

Evolution equation

Participant i at time t+1 will have probability p_i of being a speaker - and thus of increasing F_i to its maximum level MAX_i, and probability $1 - p_i$ of being a listener - thus of decreasing her happiness level by one: $F_i(t+1) = F_i(t) - 1$. Hence we have the following N-dimensional map $g(F_i)$:

$F_i(t+1) = p_i \cdot MAX_i + (1 - p_i)(F_i(t) - 1)$, for all i = 1,...,N

Fixed point and stability analysis

To find the fixed points F_i^* of each of these equations, we drop the time dependence, *i.e.*:

$$F_i^* = p_i \cdot MAX_i + (1 - p_i)(F_i^* - 1)$$

from which we get:

$F_i^* = MAX_i + 1 - 1/p_1$ for all i = 1,...,N,

which are the fixed points of the system. The fixed point F_i^* is stable when $-1 < dg(F_i^*)/dF_i^* < 1$. We have:

$$dg(F_i^*)/dF_i^* = -p_i$$

Accordingly, F_i^* is stable when $-1 < p_i < 1$, which is always fulfilled being $0 < p_i < 1$. We conclude that $F_i^* = MAX_i + 1 - 1/p_i$ is the stable fixed point of each participant. Now, a participant becomes latent when $F_i = 0$. In order for a participant to be active in the steady state, we must have $F_i^* > 0$. This translates into $MAX_i > 1/p_i - 1$ which is a restriction in the waiting time (*i.e.* patience) of agent i. Note that depending on p_i, each agent will have a different critical patience.

As an example, in our baseline model we suppose that every agent has the same probability of being a speaker. Imposing probability normalization ($\sum_{i=1}^{N} p_i = 1$), we have $p_i = 1/N$ for all i=1,...,N. In this condition an active steady state is achieved for $MAX_i > N - 1$ for all i=1,...,N. That is, in order for every participant to be active in the same conversation, their maximal waiting time cannot be less than the number of participants minus one (the participant herself). If this requirement is fulfilled, the initial conversation will, on average, be stable - the parties will remain actively involved as time evolves.

Extinction cascade and sociological interpretation

The same analysis as before can be performed iteratively. Suppose that we start at time t = 0 with N agents such that

I. $p_i = 1/N$ for all agents

II. $MAX_i > N - 1$ for i=1,..., N-1

III. $MAX_i < N - 1$ for the last agent

Then the last agent is - statistically speaking - doomed to reach latency (and eventually leave the conversation). In order to find the critical values of patience of the other agents, a similar analysis can be performed, for $N' = N - 1$, and we can conclude that the conversation will be stable if all the rest of speakers have a patience level such that $MAX_i = N' - 1 = N - 2$. This can be applied iteratively (the limit is N = 2, that leads to $MAX_i > 1$, that is, a standard turn taking conversation between two agents, as resulting from our ABM simulations). A straightforward conclusion is the following: the number of parties within a conversation will decrease until everybody feels comfortable (*i.e.* until the patience thresholds of everybody are above the critical values), and from there, it will remain as a stable conversation that every speaker will profit of.

The possible introduction of newcomers into an ongoing conversation renders a direct analytic approach, even in this very basic scenario, more difficult and goes beyond the scope of this work. Its implementation through an ABM, on the other hand, is quite straightforward. Furthermore, the analytical developments only provide insight on the steady state, *i.e.* in the limit of infinite time conversations. However, as commented above, real-time conversations only develop in finite time. Therefore, in order to focus on realistic scenarios, we should study the conversation dynamics in well-defined time windows (*transient* dynamics). In the following section we address such issues and outline the main numerical results of the agent-based simulations.

Transient dynamics

So far only the stationary states were discussed. In reality, 2-people conversation groups seem to be fairly stable, as opposed to 3-people conversation groups. It seems evident, on the other hand, that large table-wide conversations do not usually converge to a situation where sub-conversations take place mainly within 2-person conversation groups, if only because the duration of an average conversation may not be sufficient to reach that asymptotic state. We should therefore focus on the transient state. The strong model assumption of simultaneous turn taking (#2) roughly defines the characteristic time unit of the model (1 tick = 1 conversation turn) as well as the empirically-relevant range of the total number of turns taking place during a reasonable table talk. In the real world, turns are taken on average about every 10 seconds (here we deliberately obviate very short time turns, since these short turns may not have a relevant influence in the agents willingness to stay in a conversation –i.e. in their happiness status-). A one hour-long conversation then would not allow for more than about 360 turns, which is defined as the real conversation time window. Note that this information may also be used to put a lower bound on the range of permissible maximum levels of happiness. We found that, for even and odd numbers of participants larger than 5, avoidance of convergence to the stationary distribution within the first 360 turns can be achieved by setting the maximum happiness level larger than about 8 – *i.e.* this is the minimum number of conversation turns which needs to be tolerated without being entitled to speak (and therefore before leaving the conversation) to avoid precocious conversation convergence. Tables of participants with higher maximum levels of happiness would be able to maintain large conversation groups for longer periods of time.

As an example, Figure 3 shows the transient dynamics up to 376 ticks and the final stationary distribution of a model run with 15 participants and a maximum happiness level of 8. The initial table-wide conversation splits right after the beginning into 4 smaller sub-conversations because the happiness levels of some table members necessarily become minimal at the same time, and it is highly probable that some of the latents are close to another latent. The 4 smaller group conversations persist for 150 ticks before another conversation group is formed. No other conversation group is formed until 376 ticks, *i.e.* the end of the table conversation. The geometric location of, and the very participants involved in a group conversation, are persistent over time. People join or leave conversations only when they are located next to another conversation group or, in a much rarer case, when they find themselves next to a person whose happiness level has also decreased to her minimal value. Conversation groups rarely include people who are not direct geometric neighbors of other people in the same conversation. Also, latents can be trapped within a conversation group (see *e.g.* at ticks 10 and 53 in the upper left and right quarters of Table 1; latents are colored in dark grey). Finally, the typical size of a conversation group mildly fluctuates in the transient timescale, taking typical values of four people.

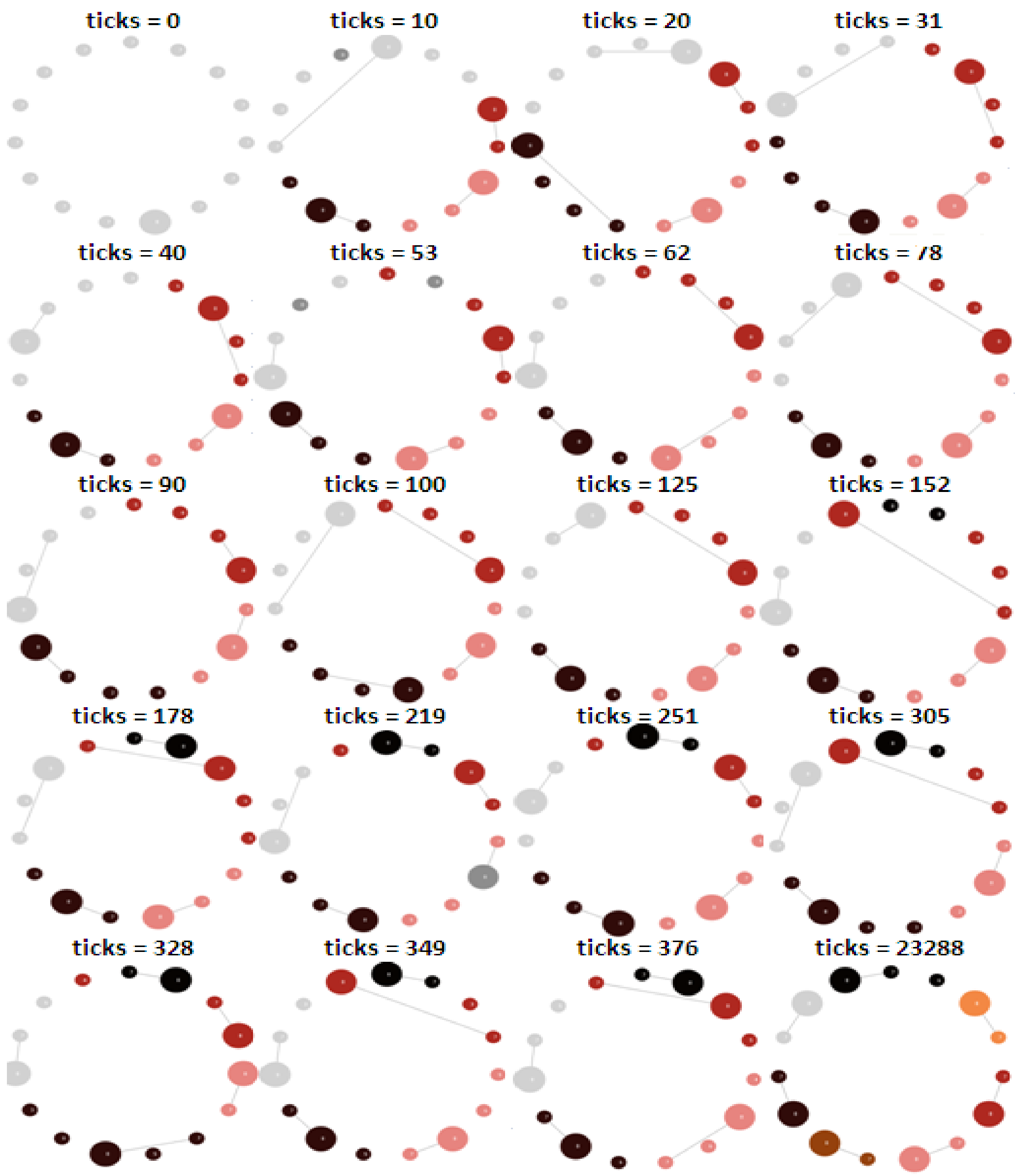


Figure 3: transition dynamics for a 15-people conversation with maximum happiness level of 8. Each agent is colored according to his belonging sub-conversation. Note that after the initial schism (first 10 steps), non-trivial schisming dynamics develops, and agents evolve hopping from a sub-conversation to another according to the evolution of their individual happiness status.

	Size of conversation group						
	15	7	5	4	3	2	
Time	Numbers of sub-conversations						Total
0	1						1
10		1			2	1	4
20			1	1	2		4
31				3	1		4
40			1	1	2		4
53			1	1	2		4
62				3	1		4
78				3	1		4
90				3	1		4
100				3	1		4
125				3	1		4
152				1	3	1	5
178				1	3	1	5
219				1	2	2	5
251				1	3	1	5
305				1	3	1	5
328			1		2	2	5
349				1	3	1	5
376				1	3	1	5
...							
23288					1	6	7

Table 1: time evolution of conversation groups for the conversation of Figure 3.

All the above findings hold in general and not only in the special illustrated example. Importantly, in spite of abstracting from conversation contents and contexts, many of these findings seem to correspond at least qualitatively to phenomena that can be observed in real table conversations. For example: table-wide conversations involving a large number of people are unstable, while smaller conversation groups persist over longer periods of time; people sometimes change conversation groups, and when this happens they confine themselves to nearby conversations (the conversational principle of least effort is the reason why party organizers often pay so much attention to the initial table population and configuration, if it is supposed to remain fixed); people within a conversation group change from time to time, but the conversation group has a tendency to remain in a specific geometric location, and only a limited number of people around the table join a specific conversation group; people who have left a conversation group may often return to that same conversation later; sometimes people would like to leave a conversation, but nonetheless they may remain in it because they are trapped between two people eagerly taking turns in that very conversation.

A fundamental conclusion can be outlined from the previous analysis: namely, that schism and nucleation of sub-conversations may be considered a dynamical mechanism that take place in conversation dynamics according to purely local rules of fitness (*i.e.* happiness status), independent of more sophisticated psychosocial or cognitive arguments.

Preliminary empirical evidence

To determine the extent to which our model replicates qualitatively or even quantitatively real-world table conversation dynamics, one should compare the predicted dynamics to large empirical data sets. While a detailed comparison is left for future investigations, we have performed a preliminary e-mail poll of 105 people (with ages in the range of $20 \div 40$) in order to roughly estimate the size of an optimal conversation group. In the survey we asked the pollees to answer to the following question:

> *In your opinion, what is, on average, the maximum number of people that can be in the same table conversation before this conversation gets uncomfortable?*

Notice that the question does not suggest a pre-determined context-based conversation, and is free from other specific sociological or cognitive characteristics, in order to reasonably fit the hypothesis of our ABM. Figure 4 shows the histogram of the answer's frequency. The maximal value for the size of a stable conversation group (N = 4) approximately matches the typical conversation group sizes upper bound that were reached in the transient state (*i.e.* in the timescale of real conversations) in our simulations - something that gives credit to our model assumptions. Further empirical data should be obtained in order to confirm these preliminary results.

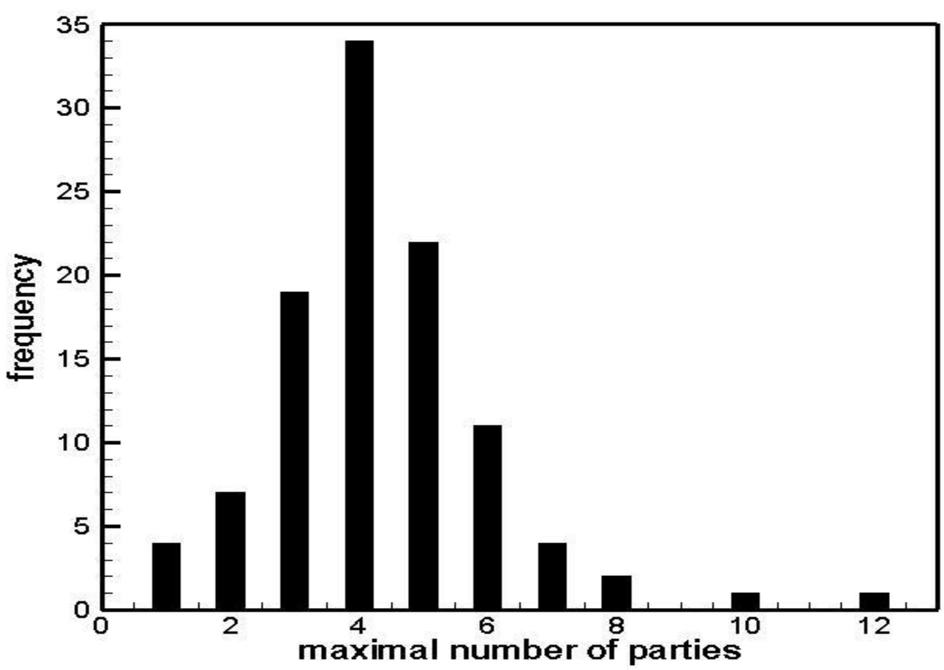


Figure 4: Histogram of the maximal number of people for a comfortable distribution (*i.e.* maximal group size for a stable conversation) according to our e-mail survey. The distribution is peaked around N = 4, in fairly good agreement with the numerical prediction of the baseline model.

Summary, discussion and future work

In spite of its simplicity and independence from psychological, social or cognitive factors, the proposed agent-based model of conversation dynamics predicts a familiar behavioral scenario:

I. Large conversation groups are unstable, while smaller conversation groups can persist for a long time. In a given time window (according to a realistic conversation duration), we may find stable conversations of more than two people. Schisming develops mainly from a balance between local rules (*i.e.* happiness status of parties) and the global characteristics (*i.e.* number of participants, target choice criteria) of the conversation.

II. The formation of new conversation groups is a relatively rare event after the initial conversation split: the conversation dynamics mainly consists of people joining and leaving already-existing conversation groups, according to non-trivial patterns. The time that each agent persists in a particular sub-conversation also fluctuates in a non-trivial way.

III. Table conversations rarely involve people who are not geometric nearest neighbors.

IV. Participants may remain trapped within their present conversation group, in spite of their dissatisfaction.

As for the (asymptotic) stationary states, we shall also note that:

V. Dyadic conversation groups are asymptotic absorbing states (thus very stable in time).

VI. The characteristic time needed to reach the stationary state scales exponentially with the maximum level of happiness, and linearly with the number of participants.

The focus of the present investigation was on the rather conservative baseline model of conversation dynamics, that originated as an attempt to model and understand the very basic mechanisms underlying dynamical and context-free schisming. Further progress in this direction depends on the matching of simulated and experimental data, which might well entail the refinement of the model assumptions.

The actual table conversation setting suggests some model generalizations that should be tackled in further research:

1. *Agents Heterogeneity and memory:* The baseline model has one control parameter (the happiness level) that can be used to fit empirical data. This also means that all agents are seen as homogenous and follow the same time-independent behavioral rules. On the other hand, it seems obvious that the large heterogeneity and variety of human behavior manifests itself also in table conversations. For example,

people in a conversation group could evoke more responses from people that are geometrically close to them. Alternatively, some people in a conversation group could follow the turn-taking within a conversation and actively try to let people speak who have not spoken for a long time and/or seem unhappy. The opposite behavior is also possible: people might tend to address people in their conversation group who have contributed recently. As this kind of behavior in the agent-based model is largely determined by the probability distribution that determines the next speaker, it is natural to allow for speaker-dependent and time-dependent probability distributions, as well as for constant updates of the same distributions to encode memory.

2. *Asynchronous character:* Inclusion of the current speaker in the probability function that determines the speaker of the next turn. This eliminates the table-wide simultaneity of turn taking, and allows a different interpretation of the characteristic time to stationarity of the system. It also removes the stability of 2-people conversations, and makes the stationary states potentially more interesting - if one further assumes that 1-person conversation group cannot socially exist, and lonely people have to join other conversation groups instead.
3. *Dynamical geometry:* Modify the conversation geometry so that parties can form conversation groups with more than only two neighbors; any number of neighbors becomes possible (reminding of *e.g.* connectivity of brain networks). A dynamic topology might eventually reproduce cocktail party dynamics.

On a more abstract level, the whole system can be described as a set of Markov chains (of high order, in presence of memory effects) or, equivalently, as a set of random walks on networks. If isolated from each other, these Markov chains are ergodic. The peculiarity of this model consists in dynamically-reconfiguring these Markov chains based on geometry and threshold levels. It describes the dynamics of interacting sub-networks where the network interaction derives from random walks taking place on these sub-networks. In this sense, it is interesting to define fixed sub-networks and allow linkage of two different sub-networks (*i.e.* let the random walk take place on the linked sub-networks) whenever one node in a sub-network reaches the lower threshold and joins another sub-network.

These generalizations might prove useful to model phenomena like volatility surges during financial crises, background noise of brain activity, split of existing communities and reformation of new ones if regular interaction/communication is absent, or validation frameworks for smart rooms algorithms - to cite but a few.

Acknowledgments

The authors would like to acknowledge the hospitality and support of the Santa Fe Institute, where part of this work was done, during the Complex Systems Summer School '09 funded by the SFI and the National Science Foundation. Special thanks go to Dan Rockmore and Tom Carter. They also thank Jordi Luque and Andrea Firrincieli for fruitful discussions. LL acknowledges financial support from Spanish grant FIS2009-13690. Finally, the authors would like to thank Chuck Brown for being a perpetual source of inspiration and funk.

REFERENCES

[1] SIMMEL G (1902) The number of members as determining the sociological form of the group, *American Journal of Sociology* 8.

[2] SACKS H, Schegloff EA, Jefferson V (1974) A simplest systematic for the organization of turn-taking for conversation, *Language* 50, pp. 696-735.

[3] EGBERT M (1997) Schisming: the transformation from a single conversation to multiple conversations, *Research in Language and Social interactions* 30 (1) pp. 1-51.

[4] GOFFMAN E (1963) *Behavior in public places. Notes on the social organization of gatherings.* New York: free press.

[5] GOODWIN C (1984) Notes on story structure and the organization of participation. In J.M. Atkinson & J. Heritage (eds), *Structures of social action*, Cambridge University Press.

[6] GOODWIN C (1987) Forgetfulness as an interactive resource, *Social Psychology Quaterly* 50, pp. 115-131.

[7] PARKER R (1984) Conversational grouping and fragmentation: a preliminary investigation, *Semiotica* 50, pp. 43-68.

[8] SCHEGLOFF EA (1995) Parties and talking together: two ways in which numbers are significant for talk-in-interaction. In P.Tenhave & G. Psathas (eds.), *Situated order: studies in the social organization of talk and embodied activities* (pp.31-42), Washington, DC: University Press of America.

[9] AXELROD R (2006) Agent-based modeling as a bridge between disciplines, in *Handbook of Computational Economics, Vol2: Agent-based computational economics*.

[10] BONO M, Suzuki N, Katagiri Y (2003) An analysis of participation structure in conversation based on interaction corpus of ubiquitous sensor data, *Proc. INTERACT 2003*, IOS Press, pp. 713-716.

[11] AOKI PM, Szymanski MH, Plurkowski L, Thornton JD, Woodruff A, Yi W (2006) Where's the "party" in "multi-party"?: analyzing the structure of small-group sociable talk, *Proceedings of the 2006 20th anniversary conference on Computer supported cooperative work.*

[12] ISHIZAKI M, Kato T (1998) Exploring the characteristics of multi-party dialogues, *Proc. ACL 1998 (vol 1)*, Morgan Kauffmann (1998), pp. 583-589.

[13] STIEFEKHAGEN R, Yang J, Waibel A (2002) Modeling focus of attention for meeting indexing based on multiple cues, *IEEE Trans. Neural Networks* 13 (4) pp. 928-938.

[14] VERTEGAAL R, Weevers I, Sohn C, Cheung C, GAZE 2: Conveying Eye contact in group video conferencing using eye-controlled camera direction, *Proc. CHI 2003*, ACM, pp.521-528.

[15] BYRNE D (1998) *Complexity theory and the social sciences: An introduction*. London: Routledge.

[16] AXELROD R (1997) *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration*, Princeton University Press.

[17] BANDINI S, Manzoni S, Vizzari G (2009) Agent Based Modeling and Simulation: An Informatics Perspective, *Journal of Artificial Societies and Social Simulation* 12 (4) 4.

[18] J. H. Miller and S. E. Page (2007) *Complex adaptive systems: An Introduction to Computational Models of Social Life*, Princeton University Press