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Modeling Behavior in Social Networks under Disagreement, in Various Logics

Dedicated to the 70 Anniversary of
Academician Constantin Gaindric

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Abstract: The simple problem I address is to determine if a set of people using fuzzy logic can arrive to a conclusion when they adopt some kind of mutual contradiction strategy. The outcome of their interaction is determined for several behaviors. Several types of models are discussed. As a side result, threshold fuzzy logic is introduced to better reflect the behavior of social network members.

Keywords: social group, aggregation, disagreement strategy, recursion, fuzzy logic.

1 Introduction

Social networks (SocNets) represent a yet poorly understood, new social process made possible by the advancement of the information and communication technologies. One of the major hurdles in understanding this process is the counter-intuitive assembling of groups of geographically disperse and intrinsically diverse subjects with diffuse or differing opinions. Despite various approaches developed in the literature, e.g. [1-9], it is not clear how such groups can coagulate and then survive despite frequent contradictions in opinions.

To help understanding the mechanics of social networks, we propose ourselves to investigate with elementary tools the simpler problem of evolution of opinion in a small group where individuals adopt a fixed strategy of mutual contradiction. Specifically, I investigate what is the outcome of disagreeing or partially disagreeing with partners in a social network under the framework of binary logic and under the framework of fuzzy logic. I aim to answer simple questions as: Is there a stable or a periodical conclusion of the interaction? How the logic influence the outcome? How long it takes to arrive to a conclusion, when a stable one is possible? How the definitions of the negation in the logic influence the outcome? What triggers a move in or out a SocNet? Assuming that a group of players in a SocNet is stable only if it reaches a conclusion in a specified time, how large can be the group, for a specified behavior of the players, for the group to survive? This paper is devoted to answer some of these questions for very simple cases as a basis for understanding more complex mechanisms of progression of groups in social networks.

The version of the paper should not be regarded as a preliminary publication that only preludes a final version.

2 A Preliminary Discussion

Social networks are established based on technology, but their operation reflects human behaviors. While statistically characterized by the number of members, member retention rate, average member visits per time unit and other similar statistical figures, these figures measure a specific social process as allowed to developing in a specified framework provided by the technology. On the other side, whenever the number of interacting players is limited and the players have to respond by stating an opinion as response to the opinions of the others in the group, human players have a limited number of options for responding to the activity of the other members in the network. Frequently, the responses must be based on the opinions of the others and can represent a logically constructed response. The group may or may not reach a conclusion supported by all members. We may assume that when a conclusion can not be reached, the group dissolves, the players are looking for another group of discussion, or leaving altogether the network. When players adopt a specific strategy of responding – possibly because of their individual interacting characteristics – the outcome may be strongly dependent on those strategies.

There are numerous questions unclear about the dynamics of social networks, including questions related to groups formation inside a social network, the stability of connections and groups, the “retention period” of individuals in the group and in the network, the migrations of players inside the network between groups, the global activity variation, the rules governing the average group dimension, and the evolution of group characteristics. Several such questions are addressed in this paper, especially how simple strategies may influence the group behavior when the strategy is played under various logics. One of the results of the analysis is that social groups are more stable when the players use non-binary logic, even when they perform in a contradiction-based strategy.

Compared to the existing literature, which deals with statistical features of the network [1, 2, 5, 6], or with topological organization of the social networks [2, 4, 6], the proposed approach focuses on logic responses only. While I do not discuss issues related to the topology of the networks, as dealt with in approaches based on graphs, as [2, 5, 9], the topology of the graph can easily be added in the developed approach.

3 Simple Logic Strategies in Small Groups

The simplest interactions between members of a group in a social network, as in typical life interaction, are based on logical operations between assessments made by the members of the group. Assuming that the members respond sequentially and that they take turns in responding with their opinion to the opinion of the other speakers, the dialogue is some logical expression in the form of a recurrence,

$$\tilde{A}_n^{[k]} = f_{n,k}\left(\tilde{A}_{n-1}^{[k]}, \tilde{A}_{n-2}^{[k]}, \cdots, \tilde{A}_1^{[k]}\right),$$

where the upper index $[k]$ denotes the turn in the recurrence (in the discussion in the group of the social network), the lower index denotes the number of the speaker, assuming n speakers, and f denotes some logic formula. The tilde sign shows that each opinion is valued under fuzzy logic by some fuzzy set. The expression may include various combinations of unions, joins and negations.

We can assume that sometimes the actors in the group use some fixed strategy; that is, they preserve the same formula from one turn to the other, making the formula to depend on the speaker, not on the turn, $f_{n,k} = f_n$. When the actors have the same response strategy, the formula does not depend on n and we are left with a true recursion formula. When the speakers preserve the formula from one cycle to the other, but they have personal forms or responding, I will say that we deal with a ring-recursion. For example, a ring recursion with three actors is expressed by $A_{n+1} = f(A_n, A_{n-1})$, where f is a logic or arithmetic expression. The use of fuzzy recursions is a tool used in several domains and was successfully applied to bioinformatics [9, 10], among others.

3.1 Logic Recursive Models

Assume a group of three players, each choosing to respond by contradicting the two others according to the behavior described by $A_{n+1} = \neg A_n \cap \neg A_{n-1}$. Again, players respond successively, taking turns. Then, whatever are the initial statements of the first two players, A_0 and A_1, the third player will respond by $A_2 = \neg A_1 \cap \neg A_0$. We assume that A_0 and A_1 are true, valid statements, for example "the apple is yellow" (A_0), respectively "the apple is green" (A_1). The answer of the third player is "the apple is neither yellow nor green" ($A_2 = \neg A_1 \cap \neg A_0$). Then, the next response will be from the first player again, who will say $A_3 = \neg A_2 \cap \neg A_1 = \neg(\neg A_1 \cap \neg A_0) \cap \neg A_1 = (A_1 \cup A_0) \cap \neg A_1$ (de Morgan), thus $A_3 = A_0$. The second player response is

$$A_4 = \neg A_3 \cap \neg A_2 = \neg(\neg A_1 \cap \neg A_0) \cap \neg A_0 = (A_1 \cup A_0) \cap \neg A_0 ,$$

thus $A_4 = A_1$. The group evolution enters into a cycle, with no conclusion reached. We can safely assume that after some time, the group disintegrates. Notice that under binary logic, any proposition (set) and its negation forms a periodic solution of the recursion,

$$p_2 = \neg p \cap \neg p = \neg p ,\ p_3 = \neg(\neg p) \cap \neg p = p \cap \neg p = \phi ,$$

$$p_4 = \neg(\phi) \cap \neg p = U \cap \neg p = \neg p ,\ p_5 = \neg(\phi) \cap \neg(\neg p) = U \cap p = p ,$$

$$p_6 = \neg p \cap p = \phi ,$$

and the result is a period-3 sequence of sets.

Consider the same responding strategy under fuzzy logic (min-max logic). Denoting the membership functions by μ and assuming the negation defined in the standard way, $\mu_{\neg \tilde{A}}(x) = 1 - \mu_{\tilde{A}}(x)$, we obtain:

$$\tilde{A}_2 = \neg \tilde{A}_1 \cap \neg \tilde{A}_0 ,\ \mu_2 = \min(1-\mu_1, 1-\mu_0) ,$$

$$\tilde{A}_3 = \neg \tilde{A}_2 \cap \neg \tilde{A}_1 = \neg(\neg \tilde{A}_1 \cap \neg \tilde{A}_0) \cap \neg \tilde{A}_1 = (\tilde{A}_1 \cup \tilde{A}_0) \cap \neg \tilde{A}_1 ,$$

$$\mu_3 = \min(1-\mu_2, 1-\mu_1) = \min(1-\min(1-\mu_1, 1-\mu_0), 1-\mu_1) ,$$

thus $\tilde{A}_3 \neq \tilde{A}_0$. The second player response is

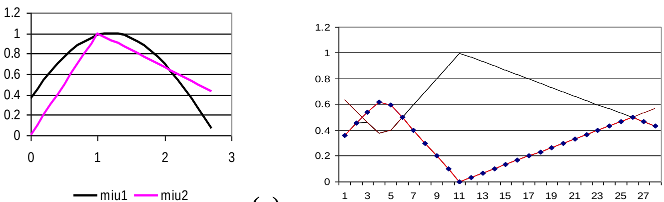
$$\begin{aligned} A_4 &= \neg A_3 \cap \neg A_2 = \neg(\neg A_1 \cap \neg A_0) \cap \neg A_0 = \\ &= (A_1 \cup A_0) \cap \neg A_0 \end{aligned} .$$

3.2 Finding Fixed Points

We look for fixed points of such iterations. Consider the recursion over fuzzy sets $\tilde{A}_{n+1} = \neg\tilde{A}_n \cap \neg\tilde{A}_{n-1}$. Assume that there is some fuzzy set $\tilde{A}$ that is a fixed set of the iteration, that is, satisfying the condition $\tilde{A} = \neg\tilde{A} \cap \neg\tilde{A}$. Then, the solutions are the sets satisfying $\tilde{A} = \neg\tilde{A}$. The only solution is obvious. Because starting with unspecified initial conditions there is no way to satisfy the condition $\min(1-\mu_n(x), 1-\mu_{n-1}(x)) = 0.5 \quad \forall x$, an equilibrium can not be reached in the iteration.

Consider $\tilde{A}_{n+1} = \neg\tilde{A}_n \cap \tilde{A}_{n-1}$, with a fixed point satisfying $\tilde{A} = \neg\tilde{A} \cap \tilde{A}$. Then, $\mu(x) = \min(1-\mu(x), \mu(x)) \quad \forall x$. When $\mu(x) > 0.5$, we should have $1-\mu(x) = \mu(x))$, which is impossible. Therefore, any set with $\mu(x) \leq 0.5 \quad \forall x$ is a fixed point. In the iteration $\tilde{A}_{n+1} = \neg\tilde{A}_n \cap \tilde{A}_{n-1}$, stability is reached if the iteration result satisfies $\mu(x) \leq 0.5 \quad \forall x$.

Examples. Starting with only two fuzzy sets, like in Fig. 1a, the result of $\tilde{A}_{n+1} = \neg\tilde{A}_n \cap \neg\tilde{A}_{n-1}$ is shown in Fig. 1b. Similarly, with the membership functions on left in Fig. 2, the result of the second order fuzzy recurrence $\tilde{A}_{n+1} = \neg\tilde{A}_n \cap \neg\tilde{A}_{n-1} \cap \neg\tilde{A}_{n-2}$ shows period 3.



(a) (b)

Figure 1. Example of periodicity in a second order fuzzy recurrence.

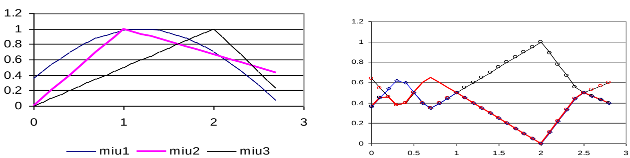


Figure 2. Example of periodicity in a third order fuzzy recurrence

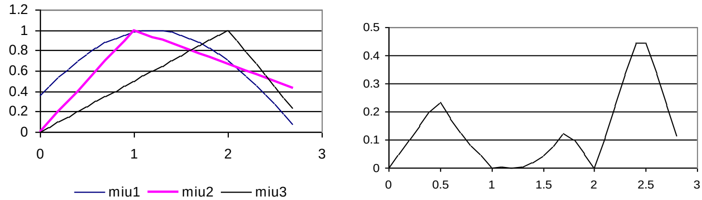


Figure 3. Stable behavior for $\tilde{A}_{n+1} = \tilde{A}_n \cap \neg\tilde{A}_{n-1} \cap \neg\tilde{A}_{n-2}$

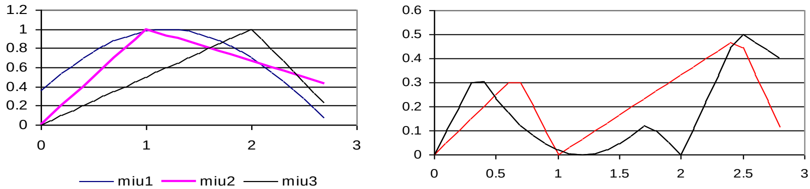


Figure 4. Results for $\tilde{A}_{n+1} = \neg\tilde{A}_n \cap \tilde{A}_{n-1} \cap \neg\tilde{A}_{n-2}$ (agree with middle).

Not negating the last response in the recurrence produces the periodical result shown in Fig. 5 below.

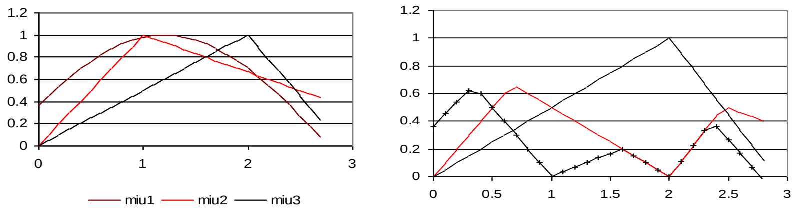


Figure 5. Results obtained for $\tilde{A}_{n+1} = \neg\tilde{A}_n \cap \neg\tilde{A}_{n-1} \cap \tilde{A}_{n-2}$.

3.3 Randomized Logic Models

While the above simple models may offer a glimpse into several facts, the purely logic models are too elementary to illuminate the complexity of human behaviors. The human response is less mechanical and is often randomly changing. In the first place, the perception of the meaning in the statements of the other members of the group may be imperfect, like as affected by some kind of noise. This type of noise translates in fluctuations of the membership functions during iteration. Also, we may assume that the "older" membership functions are noisier than the more recent ones. For example, the last membership function used in a recursion, $\tilde{A}_n$ will be affected less by noise than the membership function $\tilde{A}_{n-2}$.

Accounting for the randomness in the human response requires a "random logic" response, where the logic connectives are noisy. We define the "randomized negation" operator as $\tilde{\neg}_\alpha A = \left((1-\alpha)+\alpha\cdot rand()\right)A$, or

$$\mu_{\tilde{\neg}_\alpha A}(x) = \left((1-\alpha)+\alpha\cdot rand()\right)\cdot\mu_A(x).$$

Moreover, I define an α-randomized fuzzy set, denoted by ${}_\alpha\tilde{A}$, having the membership function

$$\mu_{\tilde{\neg}_\alpha A}(x) = \left((1-\alpha)+\alpha\cdot rand()\right)\cdot\mu_A(x).$$

Using randomized membership functions, the previously described recurrence is $\tilde{A}_{n+1} = \neg_\alpha\tilde{A}_n \cap \neg_\alpha\tilde{A}_{n-1} \cap_\alpha \tilde{A}_{n-2}$. The behavior is strongly dependent on the value α and on the distribution of the random variable *rand*(). More on the randomized logic will be presented in another paper.

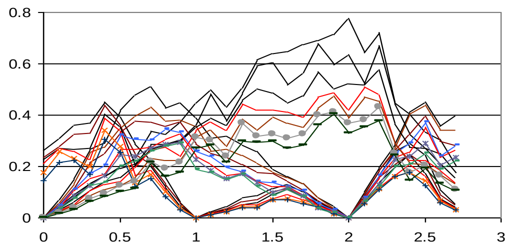


Figure 6. Effect of randomized negation with $\alpha = 0.2$, for the case shown under standard fuzzy logic in Fig. 5.

The model used in Fig. 6 is

$$A_{n+1} = \left[(0.8+rand/5)\neg A_n\right]\cap\left[(0.8+rand/5)\neg A_{n-1}\right]\cap \\ \cap\left[(0.8+rand/5)A_{n-2}\right].$$

Using higher noises (more noisy negation operator), with $\alpha = 0.4$, produces no visible pattern in the response, see below (Fig. 7).

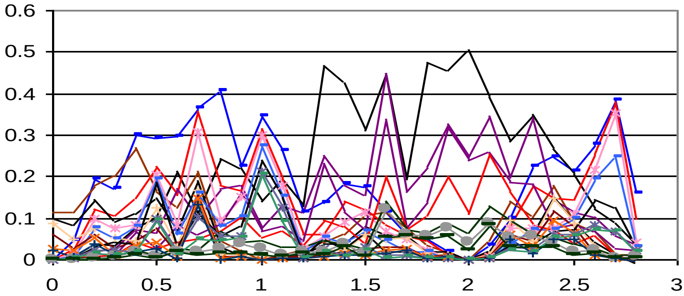


Figure 7. Effect of randomized negation with $\alpha = 0.4$, for the recursion case shown under standard fuzzy logic $\tilde{A}_{n+1} = \neg\tilde{A}_n \cap \neg\tilde{A}_{n-1} \cap \tilde{A}_{n-2}$ with the periodicity as in Fig. 5.

Using less randomization in a fifth order recursion $\tilde{A}_{n+1} = \tilde{A}_n \cap \neg\tilde{A}_{n-1} \cap \neg\tilde{A}_{n-2} \cap \neg\tilde{A}_{n-3} \cap \neg\tilde{A}_{n-4}$ produces the results shown in the next figure.

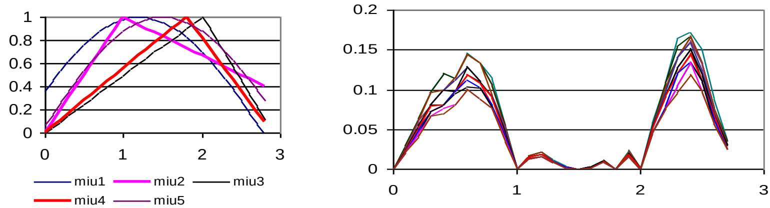


Figure 8. Results of randomized negation in the fifth order recursion.

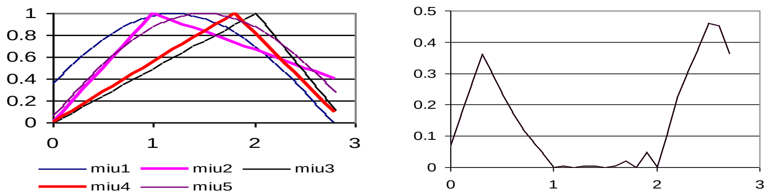


Figure 9. Result using the left-side panel membership functions as initial values for the fifth order fuzzy logic recursion $\tilde{A}_{n+1} = \tilde{A}_n \cap \neg\tilde{A}_{n-1} \cap \neg\tilde{A}_{n-2} \cap \neg\tilde{A}_{n-3} \cap \neg\tilde{A}_{n-4}$.

The recursion used in deriving Figure 8 is:

$$A_{n+1} = A_n \cap \neg A_{n-1} \cap \left[(0.9 + rand/5)\neg A_{n-2}\right] \cap$$
$$\cap \left[(0.8 + rand/5)\neg A_{n-3}\right] \cap \left[(0.8 + rand/5)\neg A_{n-4}\right].$$

When comparing the results shown in Fig. 8 with those shown in Fig.9, we notice that small changes in the randomizing logic will not much affect the result.

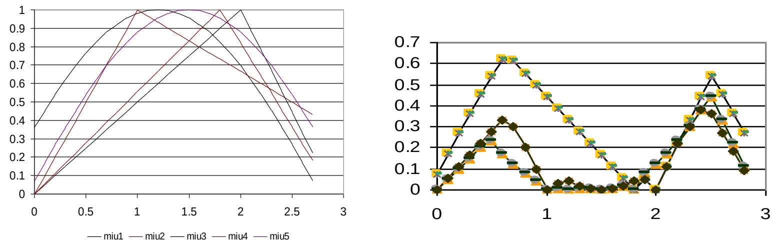


Figure 10.

In yet another example, we use the fuzzy set iteration $\tilde{A}_{n+1} = \neg\tilde{A}_n \cap \neg\tilde{A}_{n-1} \cap \tilde{A}_{n-2} \cap \neg\tilde{A}_{n-3} \cap \neg\tilde{A}_{n-4}$ where the middle term is the only one not negated. The result is shown in Figure 10 and shows that the evolution corresponds to periodicity, but the three solutions in the period are not too far from each other, so group coherence might be preserved.

4 More Realistic Models

4.1 Dynamic Population Models – Withdrawal Probability

Define a difference between solutions in a period; the distance will predict the chance of getting out by users from a group (the dissatisfaction increases with distance). Using Euclidean distance,

$$d^2(\mu_i, \mu_j) = \frac{\int_{-\infty}^{\infty} (\mu_i(x) - \mu_j(x))^2 \, dx}{\min\limits_k \int_{-\infty}^{\infty} \mu_k^2(x) \, dx}.$$

The reasoning of normalizing to the denominator is that the distance is relative – large departures from one membership function to another are significant when they are commensurate to the membership functions. Then, taking the maximum distance among all couples of membership functions, the distance of interest between the “opinions” of the members in the group is $\delta = \max_{(i,j)} d_{i,j}$. I define the probability for each member of the group to quit the group at any moment of time as $p(t_k) = 0.1 \cdot \delta_k$, where the constant 0.1 is arbitrarily chosen and may relate to the network under investigation.

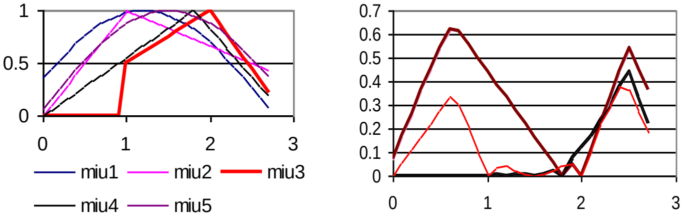


Figure 11. Result of iteration for the recursion $A_{n+1} = \neg A_n \cap \neg A_{n-1} \cap A_{n-2} \cap \neg A_{n-3} \cap \neg A_{n-4}$ with the initial membership functions shown in the left panel

What when mood oscillates? (Oscillations of the logic, of the membership function, delay-in-response oscillations etc.) How mood oscillations of an agent propagate in the network?

4.2 Weighted Logic Models

We propose a "weighted logic", or better said "threshold logic", where weights are assigned to "sources" before any inference.

In one version of the weighted logic, the weights act as thresholds. If a source has weight *w*, then whatever truth (belief) value it has under the weight, it is assigned truth value 0,

$$\theta\big(p(x), w\big) = \begin{cases} \theta\big(p(x)\big) & p(x) \geq w \\ 0 & p(x) < w \end{cases}$$

if the proposition appears in the antecedent of an inference or in a OR connected set of propositions. Thus,

$$\theta\big((p(x), w) \wedge q(x)\big) = \begin{cases} \theta\big(p(x) \wedge q(x)\big) & p(x) \geq w \\ 1 \wedge q(x) = q(x) & p(x) < w \end{cases}.$$

When the proposition appears in a join (AND connected propositions), it is replaced by

$$\theta\big(\neg p(x), w\big) = \begin{cases} 1 - \theta\big(p(x)\big) & p(x) \leq w \\ 1 - w & p(x) > w \end{cases}.$$

Thus, marginal truth is not accounted for, when the proposition belongs to a weighted source. Of course, the thresholded logic makes sense only in infinitely-valued logics, like fuzzy logic. Thresholded logic produces significantly different results in models of social networks based on fuzzy logic.

Example. Consider a version of coupled fuzzy maps (CFM) [17, 18] composed of seven agents and described by the initial conditions (initial membership functions):

$$\mu_1(x)=\begin{cases}\cos(x-1.2) & if\ \cos(x-1.2)\geq 0, x\in[1,4]\\ 0 & else\end{cases}$$

$$\mu_2(x)=\begin{cases}x/b1 & x\in[0,b1]\\ 1-(x-b1)/(b2-b1) & x\in[b1,b2]\\ 0 & else\end{cases}$$

$$\mu_3(x)=\begin{cases}(x-b1)/(b2-b1) & x\in[b1,b2]\\ 1-(x-b2)/(b3-b2) & x\in[b2,b3]\\ 0 & else\end{cases}$$

$$\mu_4(x)=\begin{cases}(x-b2)/(b3-b2) & x\in[b2,b3]\\ 1-(x-b3)/(b4-b3) & x\in[b3,b4]\\ 0 & else\end{cases}$$

$$\mu_5(x)=\begin{cases}\cos(x-1.5) & if\ \cos(x-1.5)\geq 0, \quad x\in[1,4]\\ 0 & else\end{cases}$$

$$\mu_6(x)=\begin{cases}\cos(x-2.5) & if\ \cos(x-2.5)\geq 0, x\in[1,4]\\ 0 & else\end{cases}$$

$$\mu_7(x)=\begin{cases}\cos(1.2\cdot x-3.3) & if\ \cos(1.2\cdot x-3.3)\geq 0, x\in[1,4]\\ 0 & else\end{cases}$$

The CFM equations are:

$$A_1^{[n]}=A_1^{[n-1]}\cap A_2^{[n-1]}\cap A_3^{[n-1]}\cap({}^{w=0.5}\neg)A_4^{[n-1]}$$

$$A_2^{[n]}=A_1^{[n-1]}\cap A_2^{[n-1]}\cap A_3^{[n-1]}\cap({}^{w=0.5}\neg)A_4^{[n-1]}$$

$$A_3^{[n]}=({}^{w=0.5}\neg)A_1^{[n-1]}\cap({}^{w=0.3}\neg)A_2^{[n-1]}\cap A_3^{[n-1]}\cap({}^{w=0.3}\neg)A_4^{[n-1]}$$

$$A_4^{[n]}=({}^{w=0.5}\neg)A_2^{[n-1]}\cap({}^{w=0.3}\neg)A_3^{[n-1]}\cap A_4^{[n-1]}\cap({}^{w=0.3}\neg)A_5^{[n-1]}$$

$$A_5^{[n]} = ({}^{w=0.5}\neg)A_3^{[n-1]} \cap ({}^{w=0.3}\neg)A_4^{[n-1]} \cap A_5^{[n-1]} \cap ({}^{w=0.3}\neg)A_6^{[n-1]}$$
$$A_6^{[n]} = ({}^{w=0.5}\neg)A_4^{[n-1]} \cap ({}^{w=0.3}\neg)A_5^{[n-1]} \cap A_6^{[n-1]} \cap ({}^{w=0.3}\neg)A_7^{[n-1]}$$
$$A_7^{[n]} = A_7^{[n-1]} \cap A_6^{[n-1]} \cap A_5^{[n-1]} \cap ({}^{w=0.5}\neg)A_4^{[n-1]}.$$

The result of iteration of the CFM is shown in Fig. 12.

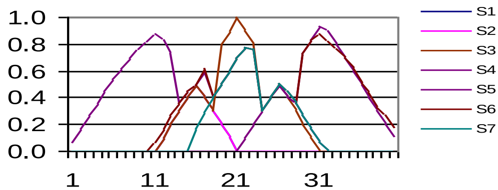


Figure 12. Result for the CFM described in the text

The result is very different from what one obtains using standard, no-threshold fuzzy logic. Indeed, the standard case produces a null result after a few iterations.

The threshold in a network may be assigned based on previous experience (learning, for example learning the degree of similar beliefs of the source and the reasoner). In a FCM, or in a vicinity based network, the weight might decrease with the distance to the source.

4.3 Partial Logic

In this subsection I sketch another aspect not yet accounted for in the behavior of human networkers. Imagine the dialogue: *A: What color do you think it is? B: I think it's blue. A: No, I don't think so*. While the dialogue is informative and perfectly valid for humans, we hardly have a suitable model for deriving a conclusion from such dialogue. The reason for it is that the "no" has not the hard negation meaning $1-\theta(x)$ where $\theta(x)$ is the truth degree of the proposition "it is blue." The dialogue says something about the object color in relation to the blue color, but says less about the true color and the rest of the spectrum of the light. *A* does not say that the object has all other colors except blue, as the hard negation implies.

Based on human meanings and experience, the dialogue can be interpreted as taking place with both speakers having a possibility to actually look at the object, because the verb "is" is in present time. Were the verb in past time, we had suspected that the speakers recollect facts and the interpretation had been "*A: I don't remember well, but I don't think so.*"

In both cases there is some sort of negation regarding blue, but a different degree of uncertainty. For sure, A is uncertain, not positive about other colors. Thus, we need to deal on a partial negation and a partial uncertainty.

4.4 Other models

While not a social network in the sense of the socializing networks on Internet, economic models involving individual human decision makers are decision aggregation problems that bear much in common to the problems above discussed. References [19] and [20] describe networks of small companies where the managers adopt competing but not necessarily logical strategies similar to the contradiction strategies described above. The results of simulations show [19, 20] that iterations of decision making based on fuzzy logic in economic processes may develop interesting dynamics.

5 Discussion and Conclusions

We attempted to introduce several simple logic models for the behavior of small groups in a social network. The models are based on fuzzy logic in its various forms. For a more accurate modeling of the human actors, several new modeling tools related to logic were needed. The new tools introduced include the thresholded logic, the approximate (randomized) logic, including randomized negation, and fuzzy coupled maps. The modeling of behavior of the actors was further improved by introducing rules for the actors leaving the group.

The main findings are i) that groups are almost always impossible when binary logic is applied and a disagreement strategy is adopted (except trivial solutions, for example when groups can survive under void agreement), moreover ii) that the groups are fragile whenever strict fuzzy logic formulas are applied to describe the group. More credible results are obtained when fuzzy logic is transformed into thresholded fuzzy logic. The models explain at least partly and superficially why the retention rate in most social networks is so low and why the grouping is more stable when the group is large. An expected, still shocking finding is that "behavioral noise", that is, small random changes in the behavior, which are quite natural in for humans, may significantly enhance the stability of the "logic social groups."

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References

[1] E. Ahmed, H.A. Abdusalam: *On Social Percolation and Small World Network*, Eur. Phys. J.B. **16**, 569-571 (2000)

[2] S. Galam: *Minority Opinion Spreading in Random Geometry*, Eur. Phys. J.B. **25**, 403-406 (2002)

[3] D.F. Zheng, P.M. Hui, K.F.. Yip, N.F. Johnson: *Herd Formation and Information Transmission in a Population: Non-universal Behaviour*, Eur. Phys. J.B. **27**, 213-218 (2002)

[4] C.M. Bordogna, E.V. Albbano: *A cellular automata model for social-learning processes in a classroom context*, Eur. Phys. J.B. **25**, 391-396 (2002)

[5] M.. Kuperman, D. Zanette: *Stochastic resonance in a model of opinion formation on small-world networks*, Eur. Phys. J.B. **26**, 387-391 (2002)

[6] P. Garcia; A. Parravano and M.G. Cosenza; J. Jimenez and A. Marcano: *Coupled Map Networks as Communication Schemes*, PACS numbers: 05.45,-a, 02.50,-r.

[7] S. Galam, S. Wonczak: *Dictatorship from Majority Rule Voting*, Eur. Phys. J.B. **18**, 183-186 (2002)

[8] M. Pasquini, M. Serva: *Clustering of Volatility as a Multiscale Phenomenon*, Eur. Phys. J.B. **16**, 195-201 (2000)

[9] J.M. Pujol, R. Sangüesa, J. Delgado, *Extracting Reputation in Multiagent Systems by Means of Social Network Topology*. AAMAS '02 Proceedings of the first international joint conference on Autonomous agents and multiagent systems: part 1. http://portal.acm.org/citation.cfm?id=544853

[10] D. Li, A. Laurent, and P. Poncelet, *Discovery of Unexpected Fuzzy Recurrence Behaviors in Sequence Databases*. Int. J. Computer Information Systems and Industrial Management Applications (IJCISIM). Vol. 2 (2010), pp. 279-288

[11] B.C.H. Chang, S.K. Halgamuge, *Approximate Symbolic Pattern Matching for Protein Sequence Data*. Int. J. Approximate Reasoning 32 (2003) 171–186

[12] J.-Y. Dieulot, P. Borne, *Inverse Fuzzy Sum-product Composition and its Application to Fuzzy Linguistic Modelling*. Vol. 14, No. 2, 2005, pp. 73-78

[13] L. A. Zadeh, *Is there a need for fuzzy logic*? Information Sciences. Vol. 178, No. 13, 2008, pp. 2751-2779

[14] A. Kolesárová, R. Mesiar, *Lipschitzian De Morgan triplets of fuzzy connectives*. Information Sciences, Vol. 180, No. 18, 2010, pp. 3488-3496

[15] K. Balazs, *Investigation of the De Morgan identities in fuzzy set theory*. Acta Technica Jaurinensis, Vol. 1, no 3, pages 513-530

[16] M. Musolesi C. Mascolo, *Designing Mobility Models based on Social Network Theory*. Mobile Computing and Communications Review, Vol. 1, No. 2, pp. 1-12

[17] Teodorescu H.N., *Information, Data, and Information Aggregation in Relation to the User Model*. In: P. Melo-Pinto, H.-N. Teodorescu and T. Fukuda (Editors), Systematic Organisation of Information in Fuzzy Systems. Volume 184 NATO Science Series III: Computer & Systems Sciences. 2003, pp. 7-10.

[18] Teodorescu H.N., *Self-organizing Uncertainty-based Networks*. In: P. Melo-Pinto, H.-N. Teodorescu and T. Fukuda (Editors), Systematic Organisation of Information in Fuzzy Systems. Volume 184 NATO Science Series III: Computer & Systems Sciences. 2003, pp. 131-160.

[19] H.N. Teodorescu, M. Zbancioc, *Two Fuzzy Economic Models with nonlinear Dynamics*, Proc. Romanian Academy, Series A, Vol. 6, nr. 1, Jan-April 2005, pp. 75-84

[20] H.N. Teodorescu, M. Zbancioc, *The Dynamics of Fuzzy-Decision Loops with Applications to Models in Economy*. Memoirs of the Scientific Sections of the Romanian Academy, Series IV, Tome XXVI, 2003, ISSN 1224-1407, pp. 299-316

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