Agent-Based Social Modeling and Simulation with Fuzzy Sets

Samer Hassan[1], Luis Garmendia[1], Juan Pavón[1]

[1] Universidad Complutense Madrid, Facultad de Informática, Ciudad Universitaria s/n, 28040 Madrid
samer@fdi.ucm.es lgarmend@fdi.ucm.es jpavon@fdi.ucm.es

Abstract. Simple models of agents have been used to study emergent behaviour in social systems. However, when considering the evolution of values in human societies, there is a need for the consideration of more complex agent models, which take into account uncertainty in human thinking. This characteristic can be addressed by using fuzzy logic in the specification of the attributes that describe agents representing individuals, the functions that model the evolution of individual change of mind, the relationships among individuals in a social network, the inheritance, and the similarity between individuals. The introduction of fuzzy logic in the models has improved the results of the simulation.

Keywords: Agent-Based Social Simulation, Agent Modeling, Fuzzy Agents, Fuzzy Logic, Intelligent Agents.

1 Introduction

Agent based social simulation (ABSS) is applied as a tool for the study of the evolution of social systems. Although this has proved successful for a considerable number of cases, simple agent models as those normally used with existing tools are not sufficient to deal with the analysis of the evolution of values in human societies. Taking, for instance, sociological surveys, such as the European Value Survey, which is run periodically, we can see that, although there is an effort to categorize the possible answers to questions such as "Do you trust political parties?", there is always a certain degree of uncertainty that has to be considered. This is even more evident when considering the evolution of values in individuals. This evolution is a consequence of multiple factors, which are strongly intertwined.

Fuzzy logic can be helpful to handle approximate or uncertainty knowledge. Here we propose to study how fuzzy logic can be useful for ABSS modeling. We analyze the different aspects that can be *fuzzificated* from an ABSS model, so it gets better adapted to reality, and more specifically to facilitate the study of the evolution of values in human societies. In concrete, this work has been applied to model and simulate the evolution of religiosity in European societies, based on a Sociology work [1]. Although this has been implemented on RePast [7], a well known ABSS tool, some additions have been made to the existing library in order to be able to model and operate with fuzzy logic attributes, and relationships.

Section 2 reviews concepts about social systems simulation, and introduces the system under study, which is taken for experimentation ideas. Section 3 introduces fuzzy logic concepts related to this environment. Section 4 presents each part of the model that is fuzzificated. Finally, Section 5 summarizes the main results and contributions of this work and issues for improving this framework.

2 Modeling and Simulation of Social Systems

Social phenomena are extremely complicated and unpredictable, since they involve complex interaction and mutual interdependence networks. A social system consists of a collection of individuals that interact among them, evolving autonomously and motivated by their own beliefs and personal goals, and the circumstances of their social environment.

A multi-agent system (MAS) consists of a set of autonomous software entities (the agents) that interact among them and with their environment. Autonomy means that agents are active entities that can take their own decisions. In this sense, the agent paradigm assimilates quite well to the individual in a social system, so it can be used to simulate them, exploring the complexity of social dynamics. With this perspective, agent-based simulation tools have been developed in the last years to explore the complexity of social dynamics. An agent-based simulation executes several agents, which can be of different types, in an observable environment where agents' behaviour can be monitored. Observations on agents can assist in the analysis of the collective behaviour and trends of system evolution. This provides a platform for empirical studies of social systems. As simulation is performed in a controlled environment, on one or several processors, this kind of tools allows the implementation of experiments and studies that would not be feasible otherwise.

There are, however, some limitations when trying to simulate real social systems. The main issue is that the individual, with regard to a software agent, is by itself a complex system, whose behaviour is unpredictable and less determined than for an agent, whose behaviour and perception capabilities can be designed with relative simplicity. Moreover, it is not possible in practice to consider the simulation of countless nuances that can be found in a real social system with respect to agent interaction, characterization of the environment, etc. For this reason, it is impractical to intend the simulation of a social system in all dimensions. On the other hand, we should and can limit to simulate concrete social processes in a systemic and interactive context. Therefore, the simulation of social systems should be considered in terms of focus on a concrete process.

In spite of these limitations, the agent paradigm offers many advantages to express the nature and peculiarities of social phenomena. However, existing agent based simulation tools promote the use of rather simple agent models, basically as a kind of cellular automata [11]. This may be valid to study emergent behaviour that results from deterministic behaviour of agents. But, when considering the evolution of complex mental entities, such as human believes and values, that approach is rather limited.

As an example of a system that requires further considerations on agent modeling, consider some sociological analysis derived from the European Value Survey and of the World Value Survey (for instance, [4]). In these surveys there are many questions about the degree of happiness, satisfaction in different aspects of life, or trust in several institutions. Although there is some kind of categorization for the possible answers, such as "Very much" "Partially", etc., there is always some degree of imprecision hardly to model with discrete categories. Even more, when the individual is evolving to different positions, some of these values get even more undefined. In order to take into account this kind of issues, fuzzy logic has been applied to model different aspects of the multi-agent system: agent attributes, functions for similarity and evolution of agent behaviour, relationships among agents in social networks, and inheritance.

3 Fuzzy Logic in this Context

Fuzzy logic is useful in vague and uncertain environments [12], as it is the case in the study of human societies. For its application in the modelling of ABSS, we have counted with the help of a sociology expert, which has been consulted repeatedly along the process.

Given a universe of discourse U, a fuzzy set $\mu: U \rightarrow [0,1]$ on the set U gives a membership degree to every element of U in the interval [0, 1].

A binary operation $T: [0, 1] \times [0, 1] \rightarrow [0, 1]$ is a *t-norm* [2][9], if it satisfies the following axioms:

1. $T(1, x) = x$
2. $T(x, y) = T(y, x)$
3. $T(x, T(y, z)) = T(T(x, y), z)$
4. If $x \leq x'$ and $y \leq y'$ then $T(x, y) \leq T(x', y')$.

The t-norms can be used to define the intersection of fuzzy sets, as follows: $\mu_{A\cap B}(x) = T(\mu_A(x), \mu_B(x)$ for all x in U. In a similar way, it can be defined the union and complements of fuzzy sets.

Fuzzy relations $R: UxU \rightarrow [0, 1]$ have many applications to make fuzzy inference in many branches of Artificial Intelligence with uncertainty, imprecision or lack of knowledge.

Let T be a t-norm [9]. A T-indistinguishability [10] relation is a fuzzy relation on a universe E, $S:ExE \rightarrow [0,1]$, satisfying reflexivity, symmetry and T-Transitivity (i.e., $T(S(a, b), S(b, c)) \leq S(a, c)$ for all a, b, c in E).

A similarity relation [13] is a Min-indistinguishability.

The classical concept of transitivity is generalised in fuzzy logic by the T-transitivity property of fuzzy relations.

The similarity fuzzy relations generalise the classical equivalence relations, so it is important to define crisp partitions of a set.

The T-transitive closure R^T of a fuzzy relation R is the lowest relation that contains R and is T-transitive. There are many proposed algorithms to compute the T-transitive closure [5].

An algorithm used to compute the transitive closure is the following:

1) $R' = R \cup_{Max} (R o_{Sup-T} R)$
2) If $R' \neq R$ then R := R' and go back to 1), otherwise stop and $R^T := R'$.

In this paper, we define fuzzy sets and fuzzy relations on the universe of individuals $U = \{Individual\}_{i=1..N}$

4 *Fuzzification* of Agent Model

The case study presented in [6] has been enriched with the use of fuzzy logic in five aspects: relationships among agents, some variable attributes that determine agent state, and functions of similarity and evolution of agent state, and inheritance. These are discussed below.

The multi-agent system in [6] defines two possible relationships among individuals (agents): *friendship* and *family*. Friendship is naturally predisposed to be fuzzified: defining friendship as a boolean (to be or not to be friend) is unrealistic, because in reality there is a continuous range of grades of friendship. Therefore, friendship is defined as a fuzzy relationship, with real values between 0 and 1.

Let $R_{friend} : UxU \rightarrow [0,1]$ be the fuzzy relation on the set of individuals that give a degree of "friendship". This fuzzy relation gives a degree of friendship for every couple on individuals in the interval [0, 1]. And the classic set Friends (Ind) is defined as all the individuals whose R_{friend}(Ind) is greater than 0.

And so and individual will have a range from true close friends to just "known" people. Of course, some restrictions to this definition could be introduced in order to suit context needs. Equivalent to friendship, we can fuzzificate the family link, although is not as trivial as before: this relationship would be closer to 1 in direct family (parents, brothers), further as the relative relation, and 0 with people whose is not family at all. Thus, R_{family} could be defined in a similar way.

On the other hand, there can be relationships that cannot be fuzzified. There is a "special kind of friendship": the couple. A stable couple can be perfectly defined as a crisp relation: you have one, or you don't. There isn't a specific process for finding a couple, so we decided to ask our sociology expert and build up a general definition for it. An agent will find a couple (always with a random possibility of failure not defined in the mathematical definitions) between the friends that have different sex, are adults and have no couple. The chosen one will be the "most compatible" one, where compatibility is defined as the aggregation of how friends are they and how similar are they. Formally:

Let $R_{has\_couple} : U \rightarrow \{true, false\}$ be the crisp relation on the set of individuals that give if an individual has couple or not. This relation is defined by:

R_{has_couple} (Ind) := (R_{couple} (Ind) $\neq$ null)

Where $R_{couple} : UxU \rightarrow \{Individual\}$ can be defined as:

R_{couple} (Ind, Ind2) := Adult(Ind) AND Ind2 = max $R_{compatible}$ (Ind,{ Ind_i ∈ Friends(Ind) where (R_{couple} (Ind_i) := false AND Sex(Ind) ≠ Sex(Ind_i) AND Adult(Ind_i))) }

Where $R_{compatible}$: UxU → {Individual} can be defined as:

$R_{compatible}$(Ind, Ind2) := OWA (R_{friend}(Ind, Ind2), $R_{similarity}$(Ind, Ind2)) = w_1 * R_{friend}(Ind, Ind2) + w_2 * $R_{similarity}$(Ind, Ind2)

An OWA (Ordered Weighted Averaging) [8] is a family of multicriteria combination (aggregation) procedures. By specifying suitable order weights (which sum will result always 1) it is possible to change the form of aggregation: for example, if we want the arithmetic average in the example OWA we can give the value 0.5 to both weights.

But here we have introduced a new concept: similarity. In the original MAS the similarity was modelled and implemented through a not normalized crude gratification algorithm, based on the amount of points gathered from the comparison of the agents' crisp attributes. By defining fuzzy sets over these variables (the attributes) and fuzzificating the similarity operator based on them we will be able to have much more accuracy in the determination of similarity between individuals. Moreover, with those fuzzy set we will be able to make inference based on them.

Therefore, we continue by defining these fuzzy sets based on the variables that define each individual. Even though there are some of them that are not fuzzificable, like the sex, the most part of them will let us define a fuzzy set over them. For example: Let $\mu_{religious}$: U → [0,1] be the fuzzy set that gives a religious grade based on the religiosity variable of the individual. This set can be defined by segments with different growth (orthodox people, moderated religious ones, agnostics, atheists…) or by a linear function. Thus, $\mu_{religious}$(Ind) = 0.2 would mean that this person is mainly not religious. The same way we could continue with other fuzzy sets.

Now, with fuzzy sets over the attributes, we can define the fuzzy similarity. For defining it we will use a T-indistinguishability, which generalizes the classical equivalences. It can be obtained from the negation of a T*-distance, as it is shown in the preliminaries. This way, aggregating the normal distance of each couple of fuzzy sets we can obtain the total similarity between two individuals:

$R_{similarity}$(Ind, Ind2)= OWA (∀μ_i defined, N(μ_i (Ind)- μ_i (Ind2)))

We can focus now on the direct interaction between the agents. In this system, we want them to influence each other in some attributes: in sex or age would be impossible, but it's logic that your ideology is influenced by your left-winged friends. This local influence is, by definition, a "fuzzy concept": how much you influence a person can't be easily quantified in any way. It's very difficult to specify this interaction, but after a deep analysis and with the help of our expert, we can dare this mathematical definition:

Let Δ_{Ind}^{X} be the variation of the attribute "X" of the individual "Ind" by all its environment. We define it as the aggregation of the influence of all its relatives, friends and couple. This influenced is determined by the "proximity" of the person, the distance between the attribute selected, and how young "Ind" is (if the agent is younger, it will be more receptive to be influenced).

Δ_{Indn}^{X} = OWA $_{i=1…N}$($R_{proximity}$(Ind_n,Ind_i) * (X_{Indn} – X_{Indi}) * μ_{young}(Ind_n))

Let $R_{proximity}$(Ind_n,Ind_i) : UxU→ [0,1] be the fuzzy relation on the set of individuals that give a degree of "proximity". This fuzzy relation is defined by the aggregation

(OWA) of the classical relation "couple" with the fuzzy relations Rfriend and Rfamily:

$R_{proximity}$ (Ind, Ind2) := OWA (R_{couple}(Ind, Ind2), R_{friend}(Ind, Ind2), R_{family}(Ind, Ind2)) = w_1 * R_{couple}(Ind, Ind2) + w_2 * R_{friend}(Ind, Ind2) + w_3 * R_{family}(Ind, Ind2)

And of course, the evolution of am attribute is determined, by each individual, as $X_{Indn} = X_{Indn} + \Delta_{Indn}^{X}$

With continuous influence the global average of the variables will change over time. But there is another source of change: demographic evolution. As time steps go on, agents will find couples and have children. Those children must inherit their parents' characteristics in a way. In the crisp MAS we solve this problem in a rough way: we obtain the new variables from the average of the parents. But now we have defined fuzzy sets based on those variables, so we can use fuzzy operators between them. Thus, we decided to use the fuzzy composition for obtaining the variables of the new individuals (mixed with a random mutation factor not included in the mathematical definition, which was introduced in favour of diversity):

$\forall$ X attribute of Ind, μ_x(Ind) = μ_x (Father (Ind)) *o* μ_x (Mother (Ind))

Another important side of the agents is their states. The state of an agent is defined by its age, and determines its behaviour. Therefore, an agent in the state of "child" cannot influence adults and cannot find a stable couple… while an "old" agent won't have children and will have more probabilities of dying. But where are the limits between states? In the crisp systems, there are threshold limits that determine that change. For example, if an agent has an age over 27, is in the "adult" state, but if it's under it, is in "young", with a radical different behaviour. This is clearly unrealistic: in reality the changes are gradual, as we are maturing. So we will apply fuzzy logic again, even though this time is quite difficult: it's easy to define how young is an individual, but it's difficult to change gradually its behaviour (anyway, it's an implementation problem, which will not be analyzed here).

The last improvement we propose is for extracting new knowledge from the system, using a fuzzy operation: the T-transitive closure. From the repeatedly application of transitive property of a relationship, it allows us to discover the influence of some variables in other "far" ones (the multiple paths of different length between those variables). This operation suits perfectly with the natural transitivity of the (fuzzy) friendship relation: the friend of my friend is not very friend of me. And so, we can infer inferior friendship grades in others. For example, if A and B are friends in a 0.8, and B and C in 0.6, we will be able to deduce that A and C are friends in a 0.48. And we could continue inferring how a D agent is friend of A, and so on. We are extracting new knowledge from the system, impossible with a crisp relation of friendship (we can't infer that A and C are automatically 100% friends).

We have imposed T-transitivity [3] of the 'friendship' fuzzy relation as a learning process of friendship of individuals with a common friend, and also as a coherence method.

The Zadeh's logic (which uses the t-norm minimum) works well, but we didn't choose it because the friendship of A and C is either the friendship of A and B or the friendship of B and C, and there is no reason for that. A and C are probably not as friend as with the common friend. This logic looses information in this context.

The Lukasiewicz logic uses the Lukasiewicz t-norm [9] defined by W(a, b) = max(0,a+b-1). It works well when the common friend is a good friend of both, but it infers no friendship when the common friend is not a very good friend of both individuals.

So, the logic we use to infer friendship is the Product logic (using the t-norm product). It works well for high and low friendship with a common friend, and it does not loose information. For example, if we have a common friend with degree ½, the product logic would decide that we are friends with degree ¼, which makes more sense that to infer a friendship degree of ½ (Zadeh's logic) or 0 (Lukasiewicz logic). In the classical world, with only 0 and 1 values, all the logics, and transitivity closure are the same, but when we dial with the uncertainty of friendship, the product logic seems to be the most similar to human reasoning.

6 Results and Conclusions

Part of the proposed fuzzification has been applied to an existing system [6]. More specifically, the *friendship* relation, but not the *family* one. Also, the compatibility concept for matchmaking, with all the restrictions, has implied changes in the similarity algorithm to a fuzzy version. Besides, we extracted new knowledge through the T-transitive closure. There is still the need to implement the fuzzy influence, the fuzzy inheritance, and the fuzzy states. With these changes, similarity operation has improve sharpness; the couples found are much more "logical" (agents know more people than before thanks to the closure, and the similarity measure is better); and the friendship is more realistic (not boolean, with grades, and considers more knowledge thanks to the T-transitive closure).

The proposed fuzzification can be applied to other ABSS systems. For instance, the example has shown how to fuzzify relations that determine agents' interactions, even mixing fuzzy and crisp values (like in the case of "influence" interaction). Also, agents' attributes can be defined in terms of fuzzy sets. Context-dependant functions, like inheritance, were modelled too, as well as a typical fuzzy similarity operation. "Life states" of agents are frequent in systems that evolve over time, especially in task solving environment. Sometimes, it is convenient to fuzzify those states. Finally, a global fuzzy operation over all the agents was defined (the T-transitive closure) on a fuzzy relation (friendship) to make inference with coherent results. Other operations could be needed and applied in a similar way.

In order to adapt these definitions to other systems, new constraints that suit context needs could be introduced. Fuzzy logic facilitates modeling to domain experts, because the linguistic terms can be easily transformed into fuzzy functions. Of course, there will be parts of an ABSS system that cannot be (or just we do not want to) fuzzified, but we think that fuzzy agents in social simulation can be extremely useful.

Future research lines that can be followed include empowering inference and approximate reasoning using fuzzy sets. Fuzzy implications represent a tool with great potential, and have solid foundations because they generalize the classic logical implication. The only special need they have is that the expert has to decide rules from his knowledge, and we must choose the operators that work well in every context. That's not an easy task, more when the field contains huge amounts of uncertainty and imprecision.

Another approach not referred here is to take into account the space and time dimensions. Even though space is implicitly covered when we let an agent to communicate only with its nearby ones, we ignore if an agent is closer than other: geography. This could be seen as another fuzzy relation, where 1 is closest neighbor, and 0 now known at all. About timing, it must be said that all the definitions here should be taken into account, because in our system continuous time does not exist: time is discretised in time steps. This way, all the operations require a step of time. For example, a right way would be: $X_{Indn}^{s+1} = X_{Indn}^{s} + \Delta_{Indn}^{X, s}$ where "s" is the number of time steps.

Acknowledgements. This work has been performed in the context of the project "Métodos y herramientas para modelado de sistemas multiagente", supported by Spanish Council for Science and Technology, with grant TIN2005-08501-C03-01.

References

1. Arroyo Menéndez, M., Cambio cultural y cambio religioso, tendencias y formas de religiosidad en la España de fin de siglo. Servicio de Publicaciones de la UCM. Madrid. (2004)
2. Flement, E. P., Mesiar, R., Pap, E.: Triangular norms. Kluwer. Dordrecht. (2000)
3. Garmendia L, Campo C, Cubillo S, Salvador A: A Method to Make Some Fuzzy Relations T-Transitive. International Journal of Intelligent Systems. 14 (9), (1999), 873-882.
4. Inglehart, R., Norris, P. Sacred and Secular. Religion and Politics Worldwide Cambridge University Press. (2004)
5. Naessens, H., De Meyer, H., De Baets, B.: Algorithms for the Computation of T-Transitive Closures, IEEE Trans Fuzzy Systems 10:4 (2002) 541-551.
6. Pavon, J., Arroyo, M., Hassan, S. y Sansores, C.: Simulación de sistemas sociales con agentes software, en Actas del Campus Multidisciplinar en Percepción e Inteligencia, CMPI-2006, volumen I, (2006), 389¬400.
7. http://repast.sourceforge.net/
8. Ronald R. Yager. Families of OWA operators. Fuzzy Sets and Systems. Volume 57, Issue 3. (1993), 125 - 148
9. Schweizer, B., Sklar, A.: Probabilistic metric spaces. North-Holland, Amsterdam, NL, (1983)
10. Valverde, L.: On the structure of F-indistinguishability operators, Fuzzy Sets and Systems 17, (1985) 313–328.
11. Wolfram, S. A new kind of science. Wolfram Media. (2002)
12. Zadeh, L.A.: Fuzzy sets. Inform. and Control 8, (1965) 338–353.
13. Zadeh, L., A.: Similarity relations and fuzzy orderings, Inform. Sci. 3 (1971) 177–200.