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Taking Into Account Imprecision in the Modeling Voter in a Multi-Agent Environment

Michel Milambu Belangany[1*], Pièrre Kafunda Katalayi[2], Eugène Mbuyi Mukendi[3]
[1,2,3] Department of Mathematics and Computer Science, Faculty of Sciences and Technology, University of Kinshasa,
[1,2,3] michel.milambu@unikin.ac.cd, pierre.kafunda@unikin.ac.cd, eugenembuyi@gmail.com

Abstract
An electoral system is a set of individuals considered as agents in a multi-agent system in which voters communicate with each other and with the environment. In such a system, it is often difficult to understand the behavior of an agent that we call a voter. This is why, in this paper, we use fuzzy set theory as an approach to model the behavior of an imprecise voter in an electoral environment. It will be just a question of presenting a model of a voter with fuzzy behavior using mathematical approaches in this environment considered as a multi-agent environment and to propose the algorithms as the tools of computer modeling.

Keywords : *voter, fuzzy voter, multi-agent system, electoral environment, modeling*.

I. Introduction

An electoral system is a complex system in which voters, candidates, and agents are involved and all of these people communicate. Such a system is considered a multi-agent system. In such a system, it is often difficult to determine a voter's position or choice with respect to a candidate's vote. In Boolean logic, an element belongs or does not belong to a given set: this is the "all or nothing". Zadeh (1965) notes that most of the time, the objects encountered in the real world do not have precise criteria of belonging. He then tried to get out of this Boolean logic by introducing the notion of weighted membership.

He defines the fuzzy set as a class of objects with a continuum of degrees of membership to this class. Such a set is characterized by a membership function that associates to each object a degree of membership between zero and one.

In the case of a specific situation, each voter is assigned to exactly one candidate, which means that the degree of membership of the voter is 1 in the case of that candidate and 0 in all other situations. Voter membership in candidates is thus mutually exclusive. On the other hand, a fuzzy voter allows belonging to several candidates at the same time; moreover, each voter has degrees of belonging that express how much this voter belongs to the different candidates.

II. Related Work

Multi-agent structures have been developed in the context of the management of complex systems such as electoral, epidemiological environments, in order to locate groups of agents, an agent in a group to monitor its behavior. These systems have allowed the understanding of areas in which there is communication, cooperation and collaboration between entities. In personality detection using context-based emotions in cognitive agents. Similarly, multi-agent systems used for search and rescue applications. Researchers have difficulty converging on an unambiguous definition of notions such as interpretation or explanation, which are often (and wrongly) used interchangeably. Moreover, despite the robust metaphors that multi-agent system (MAS) could easily provide to address such a challenge, and agent-oriented perspective on the topic is still lacking. Thus, this paper proposes an abstract and formal framework for XAI-based MAS, reconciling notions and results from the literature [6]. Online social networks are known to lack adequate support for multi-user privacy.

They present an agent architecture that aims to help users manage multi-user privacy conflicts. By considering the personal utility of content sharing and the individually preferred moral values of each user involved in the conflict, EXPRI identifies the best collaborative solution by applying practical reasoning techniques. Such techniques provide the agent with the cognitive process necessary for explicability [4].

In the race to automate, distributed systems are required to perform increasingly complex reasoning to cope with dynamic, often non-human controlled tasks. On the one hand, systems dealing with tight time constraints in safety-critical applications used to focus mainly on predictability, leaving little room for complex planning and decision making processes. Indeed, real-time techniques are most effective in predetermined, constrained, and controlled scenarios [3]. Theory of mind is generally defined as the ability to attribute mental states (e.g., beliefs, goals) to oneself and others. Building and expanding on previous work by providing an account of the explanation in terms of agents' beliefs and the mechanism by which agents revise their beliefs given the possibility [11].

As autonomous agents become more autonomous, ubiquitous and sophisticated, it is vital that humans have effective interactions with them. Therefore, these autonomous agents should be able to explain their behavior and decisions before humans can trust them. This paper focuses on analyzing human understanding of the behavior of explainable agents [1].

With the apparent societal need to design complex autonomous systems whose decisions and actions are humanly intelligible, the study of explainable artificial intelligence, and with it, research on explainable autonomous agents, a way to facilitate such studies by implementing explainable agents and multi-agent systems that (i) can be deployed as static files, not requiring server-side code execution, thus minimizing administrative and operational overhead, and (ii) can be integrated into web and other compatible user interfaces [22].

A network-oriented modeling approach for voting behavior in the 2016 US presidential election. A network-oriented computational model is presented for voting intentions over time, specifically for the race between Donald Trump and Hillary Clinton in the 2016 U.S. presidential election. Emphasis was placed on the role of social and mass communication media and statements made by Donald Trump or Hillary Clinton during their speeches. The objective was to study the influence on voting intentions and the final vote. A sentiment analysis was conducted to test whether the statements were high or low language intensity [9].

The use of adaptive temporal-causal networks to model and simulate the development of mutually interacting opinion states and connections between individuals in social networks. The focus is on adaptive networks combining the homophily principle with the plus becomes plus principle. The model was used to analyze a dataset of opinions on alcohol and tobacco use and friendship [18].

In recent years, social networks have been increasingly used to study political opinion formation, monitor election campaigns, and predict election outcomes, as they are capable of generating a huge amount of data, usually in textual and unstructured form. The authors aim to collect and analyze data from Twitter messages identifying emerging trends in topics related to a constitutional referendum that recently took place in Italy in order to better understand and predict its outcome [17].

Competitive multi-agent systems (MAS) are inherently difficult to control due to agent autonomy and strategic behavior, which is especially the problem when there are system-level goals to achieve or specific environmental states to avoid. Existing solutions for this task mainly assume specific knowledge about agents' preferences, utilities and strategies, neglecting the fact that actions are not always directly related to agents' true preferences, but may also reflect the anticipated behavior of competitors, be a concession to a superior adversary or simply be intended to deceive other agents. The authors propose a new approach to governance of competitive MAS that relies exclusively on publicly observable actions and transitions, and uses the knowledge gained to deliberately restrict the action spaces, thereby achieving the system's goals while preserving a high level of autonomy for the agents [13].

In A New Complex Fuzzy Inference System with Fuzzy Knowledge Graph and Extensions in Decision Making, the authors say that, Complex fuzzy theory has strong practical implication in many real-world applications. Complex Fuzzy Inference System (CFIS) is a powerful technique to overcome the challenges of uncertain and periodic data [10].

In Complex Cubic Fuzzy Aggregation Operators With Applications in Group Decision Making, The Cubic Set and Complex Fuzzy Set are presented as two useful tools that have been successfully used to deal with fuzziness and uncertainties (Xiaoqiang, Yameng, Zichang, Feng & Wu, 2020). In Formalizing fuzzy control in possibility theory via rule extraction shows that possibility system has recently been recognized as a potential foundational theory for fuzzy theory. Set theory although the concept of possibility is derived from the membership function of fuzzy sets. As an application of fuzzy set theory, fuzzy control has been widely used in engineering practices, where the control of laws is described by fuzzy if-then rules [20].

In real life, there will be many uncertainty problems, one of which is due to the vagueness of the concept of things, i.e., it is difficult to determine whether an object conforms to the concept. This situation largely exists in some states, phenomena, parameters and interrelationships between things. For such uncertain events with heavy subjective influencing factors and incomplete data, fuzzy methods should be used to cope with them [11]. None of the aforementioned works have used fuzzy sets in the electoral domain. In this paper, an agent is a voter, a candidate in an electoral environment capable of speaking or expressing an opinion with different agents on an occasion within the environment and perceiving its environment, manipulating the objects in the environment including the election kits. Referring to the expression of opinions, it can be said that some voters have an imprecise opinion. These kinds of voters are fuzzy voters who are even the subject of this article in which we model the behavior of a fuzzy voter based on his imprecise language.

III. Methods

1. Material

In this article, we used Anaconda Navigator as a utility particularly jupyter to manipulate the libraries of the python language in particular Matplotlib which is a python library which allowed us to visualize the data and to draw the curves [16].

Numpy is a python library that contains functions related to the manipulation of our data which are represented in matrix form (two dimensional arrays, vectors)[16]. Etc..., the draw.io environment to represent the electoral system composed of individuals (voters, candidates and agents ...). The notepad that contains the data used and the MS Excel that allowed us to organize the data and compare the curves.

2. Methods

We use the theory of fuzzy subsets which will allow us to present the imprecise behavior of a voter in an electoral system. Let X be a reference set and let x be any element of X. A fuzzy set A of X is defined as the set of couples :

$$A = \{(x, \mu_A(x)), x \in \mathrm{X}\} \quad (1)$$

Where :

$$\mu_A: X \rightarrow [0, 1] \quad (2)$$

Thus, a fuzzy set A of X is characterized by a membership function that associates, to each element x of X a real in the interval [0, 1]; $\mu_A(x)$ represents the degree of membership of x to A. Thus, the closer the value of $\mu_A(x)$ is to unity, the higher the degree of membership of x to A [2].

If we have:

$\mu_A: X \rightarrow \{0, 1\}$ We find the Boolean case:

Either x belongs to $A(\mu_A = 1)$
Or it does not belong to $A(\mu_A = 0)$.

And the following case is very useful in the sense that an element belongs partially:

Let x belong partially to $A(0 < \mu_A(x) < 1)$

It is important to specify that the fuzzy set is considered as empty if the membership degrees of all the elements of the universe are all equal to zero.

$$A = \emptyset \Leftrightarrow \mu_A(x) = 0, \quad \forall x \in X \quad (3)$$

Two fuzzy sets are equal if their membership degrees are equal for all elements of the reference set, i.e., if both fuzzy sets have the same membership function [5].
Two fuzzy sets A and B, defined on the same reference set X are equal if:

$$\mathrm{A} = \mathrm{B} \Leftrightarrow \mu_A(x) = \mu_B(x), \forall x \in \boldsymbol{X} \quad (4)$$

a. Modeling

This complex system in Figure 1 we call the electoral system which is composed of individuals who communicate. To model a fuzzy voter, we use the theory of fuzzy subsets as below:

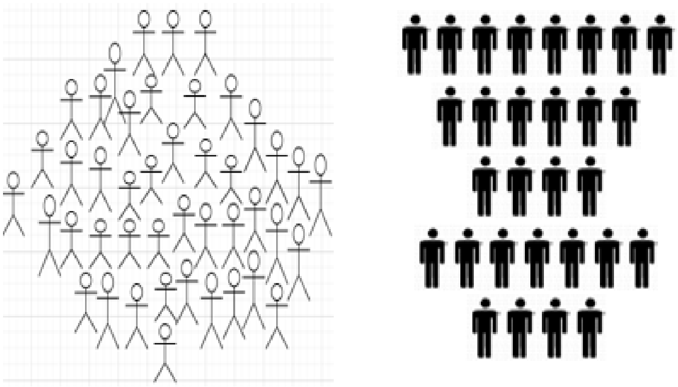

Figure 1. Complex system composed of the voters.

Thus, referring to the theory of fuzzy subsets above, our model can be represented as follows:

$$\mu_{E_f}(e) : S_e \to [0, 1] \quad (5)$$

Where :

S_e:Universe of discourse or Reference Set
e : voter (any element of S_e)
E_f :fuzzy subset of S_e
$\mu_{E_f}(e)$:Membership function that measures the degree to which e belongs to E_f

We then define this membership of a voter by :
$\mu_{E_f}(e) = 1$ if e belongs completely to E_f
$\mu_{E_f}(e) = 0$ if e does not belong to E_f
$0 < \mu_{E_f}(e) < 1$ if e belongs partially to E_f
Taking the array of fuzzy values T_{vf} of size n from which each part can be removed as a vector of the fuzzy values of a voter below:

Table 1. Matrix of fuzzy membership values for voters

$\boldsymbol{e_1}$	**0.0000**	**0.01**	**0.04**	**0.02**	**…**	**0.3**
$\boldsymbol{e_2}$	0.1	0.006	0.03	0.05	…	0.005
$\boldsymbol{e_3}$	1	1	1	1	…	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮
$\boldsymbol{e_m}$	0.007	0.07	0.7	0.8	…	0.9

b. Proposal of the algorithms

	Proposal algorithm
INPUT	$S_e = \{e_{1,}e_2, \dots, e_n\}$; $Q_f = [0,1]$; E_f
	Begin
1.	Repeat
2.	For i = 1 to n do
3.	Read : $\{S_e\}$
4.	The fuzzy quantifier Q_f Fuzzyfie the $\{e_i\}$
5.	If $0 < \mu_{E_f}(e_i) < 1$ Then
6.	$e_i\ admits\ several\ candidates$
7.	$e_i\ is\ fuzzy$
8.	Endif
9.	Endfor
10.	End repeat
11.	End.

The second proposed algorithm on the fuzzy behavior of a voter is the following:

fuzzy voter algorithm	
INPUT	$T_{vf} = \{v_{f1,}v_{f2}, \dots, v_{fn}\}$, $S_e = \{e_{1,}e_{2,} \dots, e_m\}$, E_f
Begin	
1.	Repeat
2.	For i = 1 to n do
3.	If $T_{vf}[i]\ is\ different\ to\ T_{vf}[i+1]$ Then
4.	$e_i\ is\ fuzzy$
5.	$f_{E_f}(e_i) \neq f_{E_f}(e_{i+1})$: so it is fuzzy
6.	Else
7.	$f_{E_f}(e_i) == f_{E_f}(e_{i+1})$: is not fuzzy, $\forall e_i \in S_e$
8.	Endif
9.	EndRepeat
10.	End

IV. Result and Discussion

The imprecision zone is the part covered by the fuzzy voters, while the precision zone contains the voters with a precise choice.

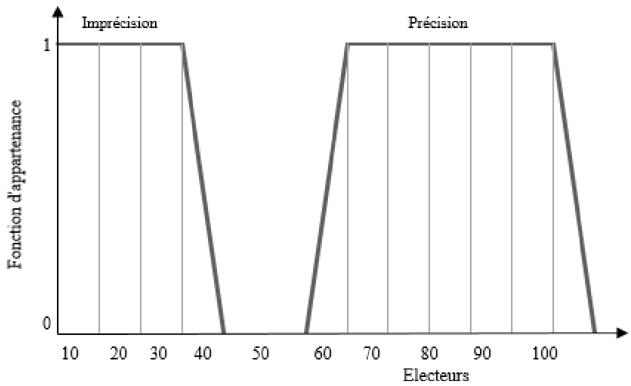

Figure 2. Distribution of voters

The representation of the fuzzy part of voters in the figure below :

Figure 3. The fuzzy voters

Fuzzy behavior of voters represented by two curves of which in blue the language of the voter is totally fuzzy and in red the language of the voter is partially fuzzy

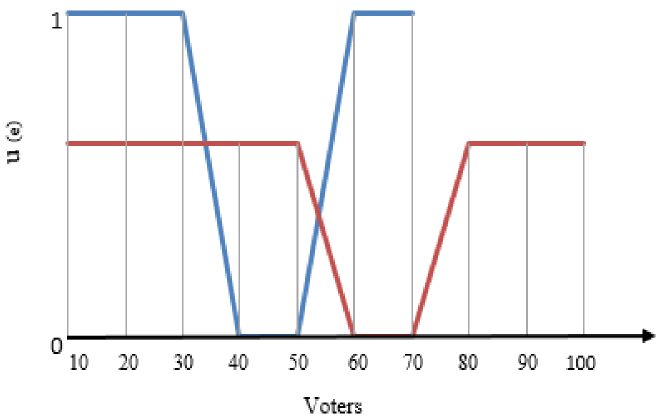

Figure 4. The fuzzy voter membership function

$$\mu_{e_i}(L_f) < 50 : then\ the\ voter\ is\ fuzzy$$
$$\mu_{e_i}(L_f) = 50 : Then\ the\ voter\ does\ not\ belong$$
$$50 < \mu_{e_i}(L_f) \leq 100 : Then\ the\ voter\ totally\ belongs$$

$$If\ L_f = 50:\ \mu_{e_i}(L_f) = 0$$
$$If\ L_f < 50 \le \mu_{e_i}(L_f)\ :\ \frac{\mu_{e_i}(L_f) - L_f}{\mu_{e_i}(L_f) - 50}$$
$$If\ L_f \ge 60:\ \mu_{e_i}(L_f) = 1$$

Where :

$\boldsymbol{L_f}$: $fuzzy\ langague$

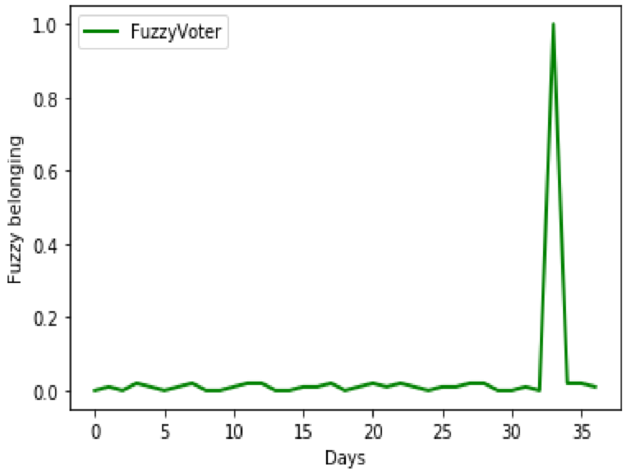

Figure 5. Behavior of a fuzzy voter over the course of a day

Figure 5 above, presents the evolution of the membership behavior of a fuzzy voter by day, i.e. each day he has a position for each candidate. In fact, looking at this figure, at the beginning this voter does not accept any candidate, then he tries to give a position for the first candidate at 0,01 and the following day 0,02 for another one the third day he gives less than 0,01 to the starting candidate therefore each day his position changes at the thirty second day he gives a position with a total membership of 1 and after he changes his value again therefore he does not have a total membership.

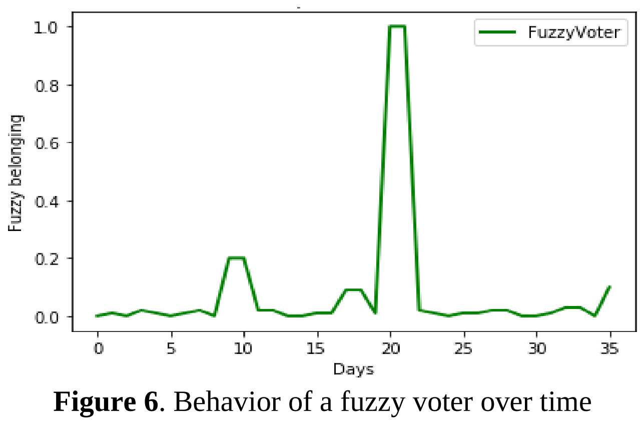

Figure 6. Behavior of a fuzzy voter over time

In this figure 6, the fuzzy agent or voter shows different positions every 5 days interval. As we can see in this figure 6 where it rises with a position of 0.2 for a candidate and after the next few days it falls to less than 0.2 for another candidate. So for each interval of 5 days there is a position of this voter that is different from the previous one that makes him a fuzzy voter.

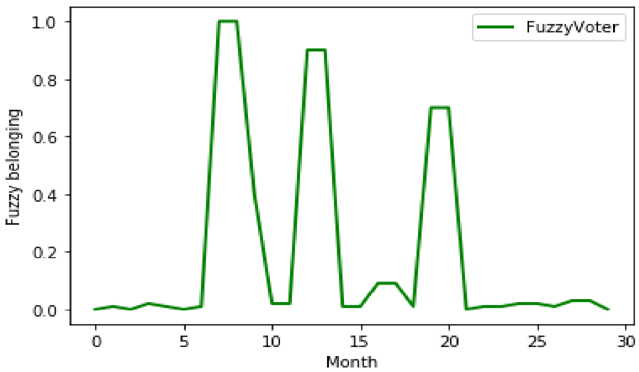

Figure 7. Behavior of a fuzzy voter over the course of a month

In this figure 7, the voter fumbles over an interval of months taking different positions on the different candidates. Here, a voter blurs in the first three months his position is below 0.2 for the candidates and the last two months in the interval of 5 months he is below 0.1 and in the next interval he belongs totally to one candidate with 1 in the interval of 10 to 15 months, he makes 0.9. So for each interval of months it changes positions several times. And finally of account in interval of months it changes values of measure of degree of confidence to the candidates. We will notice that, this voter is inconstant. Therefore, he is a fuzzy voter whose behavior is imprecise.

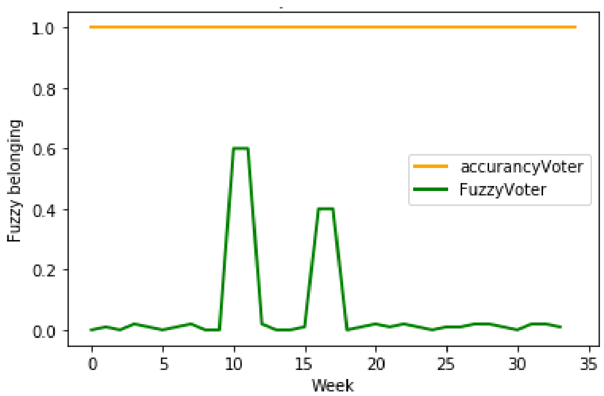

Figure 8. Behavior of a fuzzy voter and a normal voter

In this figure 8, we see the behavior of a fuzzy voter and a normal or accurate voter. Looking at this figure, the fuzzy voter seems to be unstable or imprecise because it changes its behavior over time so for each sequence of weeks it displays some behavior. On the other hand, a precise or normal voter remains constant by keeping a certain position during all the weeks. For this purpose, it is necessary to identify the electoral environment in which a voter evolves after having noted among many voters that not all of them are stable, i.e. have a well defined position.

V. Conclusion

This article focused on the consideration of the imprecision in the modeling of a voter in order to be able to follow his behavior throughout an electoral process. It was in fact a question of being able to use the theory of fuzzy subsets in order to present a model capable of defining or showing the evolution of the behavior of a voter with respect to the candidates in an electoral system. The use of imprecision in this modeling showed that during an electoral process a voter can be imprecise in the sense that every day, every week or every month he has a thought about the candidates with a certain value of his membership function which defines the degree of confidence of this voter with regard to the candidates. This approach offers significant advantages using our algorithms proposed in this article to assure election candidates that not everyone who follows you is necessarily your voter because as he follows you so he follows another candidate. So for each candidate, a fuzzy voter has a confidence measure value that we call the candidate membership function of a fuzzy voter that can change by day, week or month so that on the day of the vote the voter can go without a specific choice of candidate.

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