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Multiagent Systems as an Approach to Building Fuzzy voter Communities using fuzzy languages

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Abstract

This paper explores the use of fuzzy set theory to model the behavior of voters in a multi-agent electoral environment. Voters, represented as fuzzy agents, communicate using imprecise language to form communities based on shared linguistic terms. By leveraging graph theory, we construct a model of a fuzzy voting system where agents are linked based on the similarity of their fuzzy language. The proposed approach focuses on identifying, constructing, and extracting communities of fuzzy voters without delving into their relational dynamics. Using fuzzy set membership functions, we define linguistic variables that reflect the imprecision in voter behavior. The study introduces an algorithm to detect communities by creating links between fuzzy voters, ultimately forming groups based on their linguistic similarities. Results demonstrate that fuzzy communities can be successfully constructed, where the membership function quantifies the degree of belonging of voters to specific communities. This method contributes to a better understanding of voting behavior in complex, heterogeneous systems and offers a novel approach to community detection in multi-agent systems.

Keywords : *Fuzzy Language, Multiagent Systems, Community, Construction And Voter*

I. Introduction

In this article, a community is formed of voters or agents who speak the same language, in our case it is the fuzzy language that concerns us to create links and form community of fuzzy voters. Referring to the article on Taking into account imprecision in the modeling voting in a multi-agent environment [1], in which he defines 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 [1], there is reason to identify or build community by creating links between vague voters based on their languages without worrying about their relationships. some authors have used the term community, multi-agent system in particular: Complex networks have a large number of nodes and edges, which prevents the understanding of network structure and the discovery of valid information. This paper proposes a new community detection method for simplified networks. First, a similarity measure is defined, the path and attribute information can reflect the potential relationship between nodes that are not directly connected [2].

Community detection aims to discover hidden community or groups in complex networks and is essentially unsupervised clustering behavior. However, most of the existing unsupervised methods are designed for homogeneous networks; therefore, they cannot effectively handle heterogeneous structures and rich semantic information. Under such a situation, it is difficult to accurately detect community in heterogeneous networks that better reflect the real world [3]. A community is a set of nodes in a network where the density of connections is high [4].

Using this definition on the real world around us, we can confirm that an electoral system is a multi-agent system. The voting system employed by several countries or states is considerably a typical example of a multi-agent system. Indeed, we can specify the set that characterizes this system. In this paper, the consensus problem of heterogeneous multi-agent systems under directed topology is investigated [3],[4]. Specifically, this system is composed of three classes of agents respectively described by first-order, second-order and third-order integrator dynamics [5],[6].

By the aid of linear filter, graph theory and matrix theory, the consensus problem is realized based on the two proposed consensus protocols [7],[8]. Moreover, group consensus can also be solved by adjusting parameters. This theory applicated in simulating spatiotemporal dynamics of urban underground space development using multi-agent system: A case study in Changzhou City, China [9],[10]. Consensus-Based Distributed Connectivity Control in Multi-Agent Systems, in this paper it present distributed connectivity control problem in networked multi-agent systems [11],[6]. The system communication topology is controlled through the algebraic connectivity measure, the second smallest eigenvalue of the communication graph Laplacian [12],[13]. The algebraic connectivity is estimated locally in a decentralized manner through a trust based consensus algorithm, in which the agents communicate the perceived quality of the communication links in the system with their set of neighbors [14],[15].

II. Methods

In our article, we will use this notion from graph theory to allow us to create links between imprecise voters which we otherwise call fuzzy voters.

Thus, a graph G is made up of two sets [2] :

1. A Set X = (x_1, x_2, …, x_n) of elements called vertices or nodes, materialized by points:
2. A Set U = (u_1, u_2, ..., u_n) of ordered pairs (i,j) with i ∈ X and j ∈ X. The elements of this set are called “arcs” or “branches”

A graph is therefore noted G = (X, U).

But, in this article we will note C = (E, L):

1. A Set E = (e_1, e_2, …, e_n) elements called fuzzy voters or agents, materialized by agents:
2. A Set L = (l_1, l_2, ..., l_m) of ordered pairs (i,j) with i ∈ E and j ∈ E. The elements of this set are called “links” or “relations”.

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 (Milambu, Kafunda & Mbuyi, 2024) :

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

Where :

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

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 [16].

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.

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

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 [17].
Two fuzzy sets A and B, defined on the same reference set X are equal if:

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

Inclusion

$$A \subseteq B \Leftrightarrow \forall x \in E, \mu_A(x) \leq \mu_B(x) \tag{5}$$

Union

$$A \cup B = \max\left(\mu_A(x), \mu_B(x)\right)), \forall \mathrm{x} \in \mathrm{E} \tag{6}$$

Intersection

$$A \cap B = \min\left(\mu_A(x), \mu_B(x)\right)), \forall \mathrm{x} \in \mathrm{E} \tag{7}$$

$\bar{A}$: is said to be complementary to A if its membership function satisfies:

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x), \forall x \in E \tag{8}$$

The reference set of a natural language word is called the Discourse Universe. The One-Word Discourse Universe is a set of terms that evoke the same concept but to different degrees. It may or may not be finished [18].

a. Linguistic Variable

A linguistic variable represents a state in the system to be adjusted. Each linguistic variable is characterized by a set such that:

$$\{v, E(v), U, R, S\}$$

Or :
v:is the name of the variable
E(v): is the set of linguistic values that v can take
U:is the Universe of discourse associated with the base value
R: is the syntactic rule to generate the linguistic values of v
S: is the semantic rule to associate a meaning with each linguistic value [19].
For the case of this thesis, the model is as follows:
The linguistic variable ***v*** = candidate choice
This variable can be defined with a set of terms

1) E(v) = {good, very good, extremely good, not very good, bad, very bad, extremely bad, little bad}: Which form his Universe of discourse
2) U = [0%, 100%]
3) The basic value is the choice of the candidate
4) The term “good” represents a linguistic value

It can be interpreted as:

“Choices greater than 50%”
“Choices smaller than 50%”

b. Linguistics of a voter

Below we present some vague words from voters:

1) We will see;
2) I could vote good candidate;
3) I see x doing but y also sometimes z;
4) I can vote x good! We'll see because, yes too but z had done well in all ways I don't know yet who to vote for.
5) I'm not interested in this yet
6) I want to see first [20],[28].
7) Etc…

$$Lang_{e_i} = \{m_1, m_2, \dots, m_p\}$$

With :

$Lang_{e_i}$: $voter\ language$

m_i : words or terms used by a voter

c. Algorithm Proposal

Table 1. Algorithm Proposal

	Algorithm proposal	
1.	Parameter	$Lang_{e_i} = \{m_i\}$ and $Lang_{e_j} = \{m_j\}$ / i=1,2,…, n and j=1,2,…,p
		$V_{Linguistics} = choice$, $T(choice) = \{t_1, t_2, \dots, t_n\}$
2.	Output	$C = (E, L)$ / C is community, E is voters set and L is link
3.		REPEATE
4.		For i = 1 to n do
5.		For j = 1 to p do
6.		$E = \{e_i, e_j : e_i\ and\ e_j\ is\ voters\}$
7.		If $\mu_L(l(e_i)) = \mu_L\left(l(e_j)\right)$, $\forall l(e_i), l(e_j) \in U$ Then
8.		Create the link between $e_i\ and\ e_j$
9.		$L = \{e_i e_j \in ExE\}$
10.		affect them in C_k /
11.		Else no link
12.		End if
13.		End.

Table 2. The Matrix of decision

	$VL_{e_j}.t_j$	$VL_{e_{j+1}}t_{j+1}$
$VL_{e_i}.t_i$	Vf	Vf
$VL_{e_{i+1}}.t_{i+1}$	Vf	Vf

This table is a matrix representing the links between voters with fuzzy language. The link is only possible between voters if these voters use vague terms about their choices [21],[22],[23],[24].

III. Results and Discussions

We thus open the discussions by presenting the different results obtained on the construction of community based on fuzzy voters. A community built from fuzzy voters is also fuzzy.

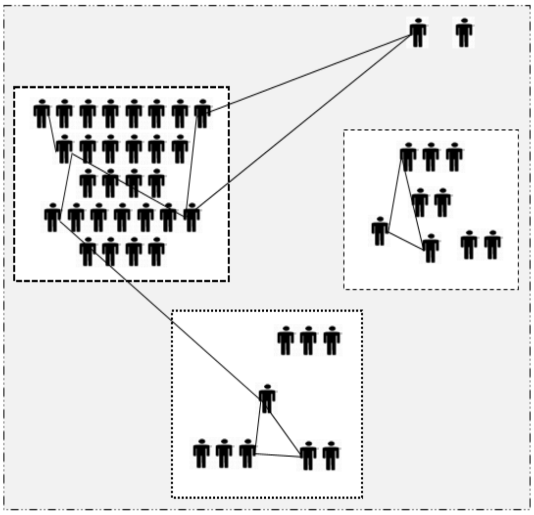


Figure 1. Identify of community

The identification of community of voters with the same imprecise language in the choice of candidates in a population of voters.

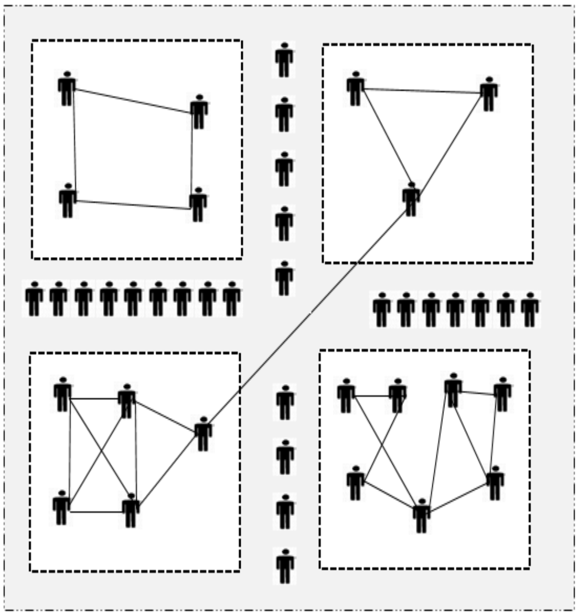


Figure 2. Extract of voters groups

The fuzzy voters are grouped according to whether they use the fuzzy terms in order to build community and the other ungrouped ones do not interest us because they have a precise choice [26],27].

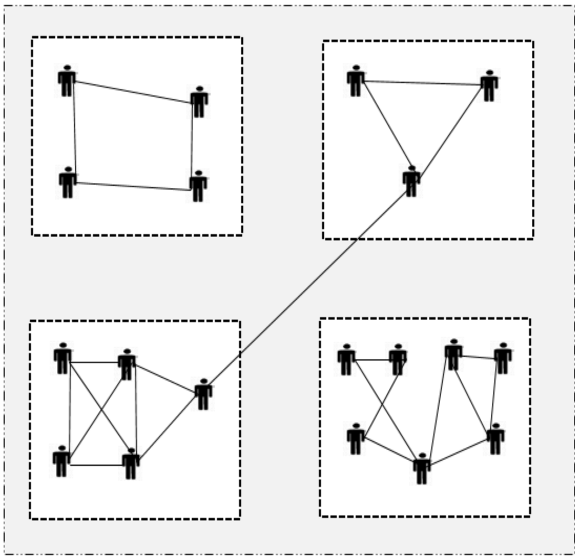


Figure 3. community trained

As we can see in the figure above, the Extraction of fuzzy community from fuzzy voters.
The membership function gives a value of 0.3 for a community of fuzzy voters whose language revolves around percentage 30 to 40.

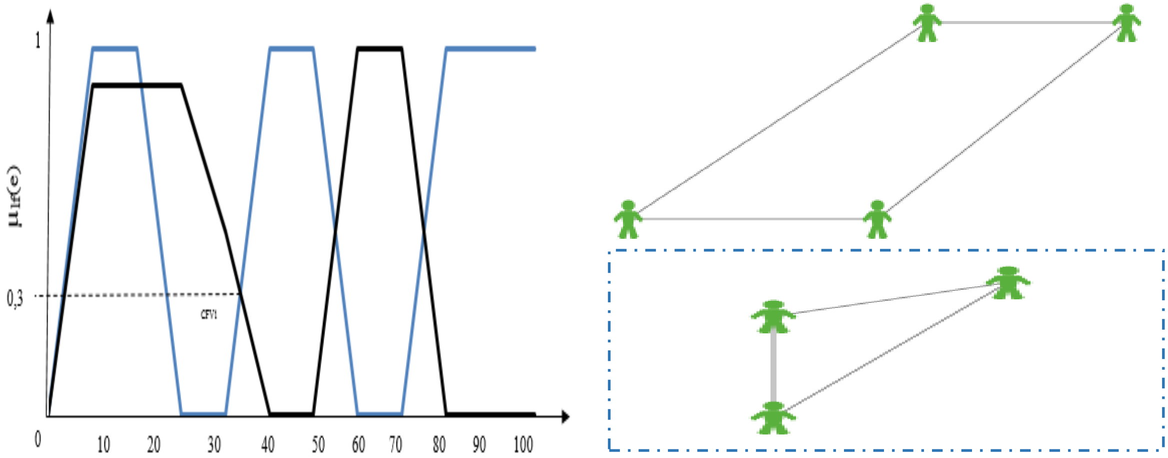


Figure 5. degree of belonging to a vague community

We present a figure or diagram of fuzzyfication and defuzzyfication from classical language to fuzzy language and from fuzzy to classical language below. In this diagram, we have as input the classical language which is fuzzyfied taking into account the linguistic variable and all the terms associated with the different fuzzy rules.

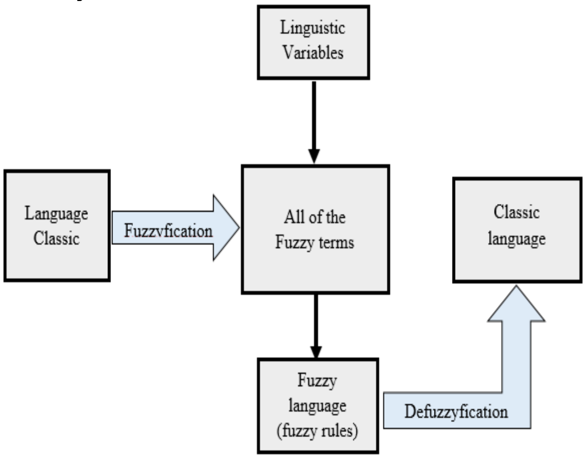
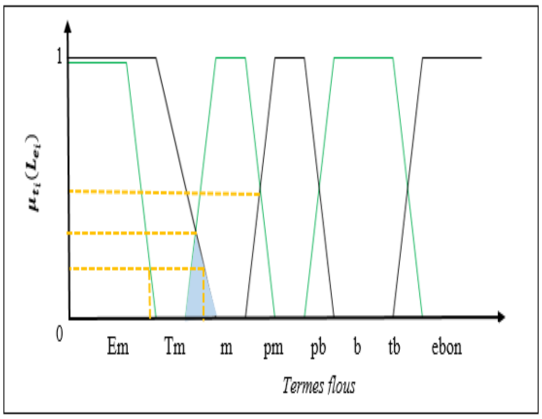


Figure 6. fuzzyfication and defuzzyfication scheme



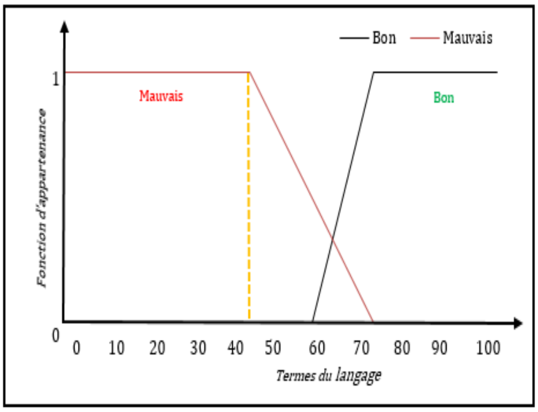


Figure 7. degree of belonging of fuzzy term. **Figure 8.** degree of belonging two fuzzy terms

Table 2. Fuzzy Matrix Cognitive

		Choice	
		Bad	Good
Choice	Bad	B	G
	Good	G	G

IV. Conclusion

This article is a continuation of the publication on taking into account imprecision in a voter's behavior. It was therefore a question of this article proposing an approach for constructing community of fuzzy voters based on the terms used in the language of voters. Throughout this article, we have used agents to represent the community of these so-called vague voters. We focused on the identify, construction and extraction of fuzzy community as presented in the different figures of this article.

The use of this approach makes it possible to construct groups of voters without seeking to know the relationships between voters, but only exploit their languages in order to identify and construct communities based on the proposed algorithm.

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