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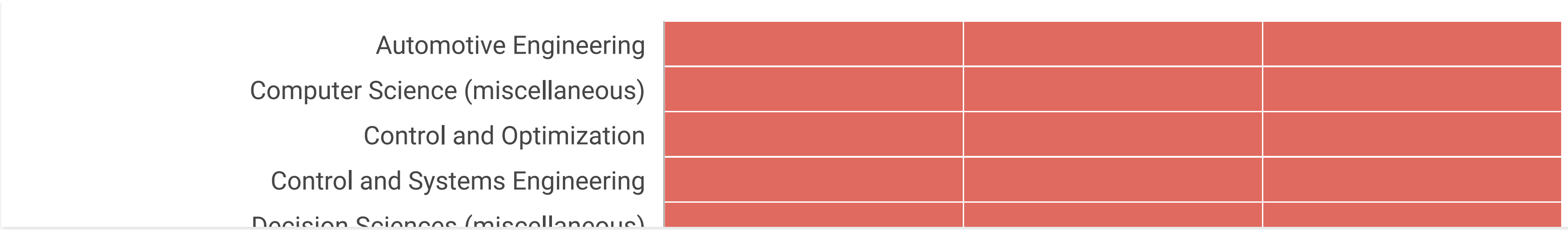

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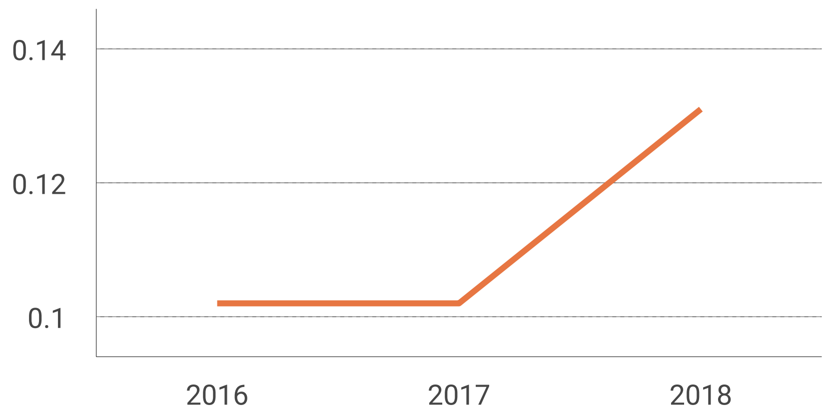

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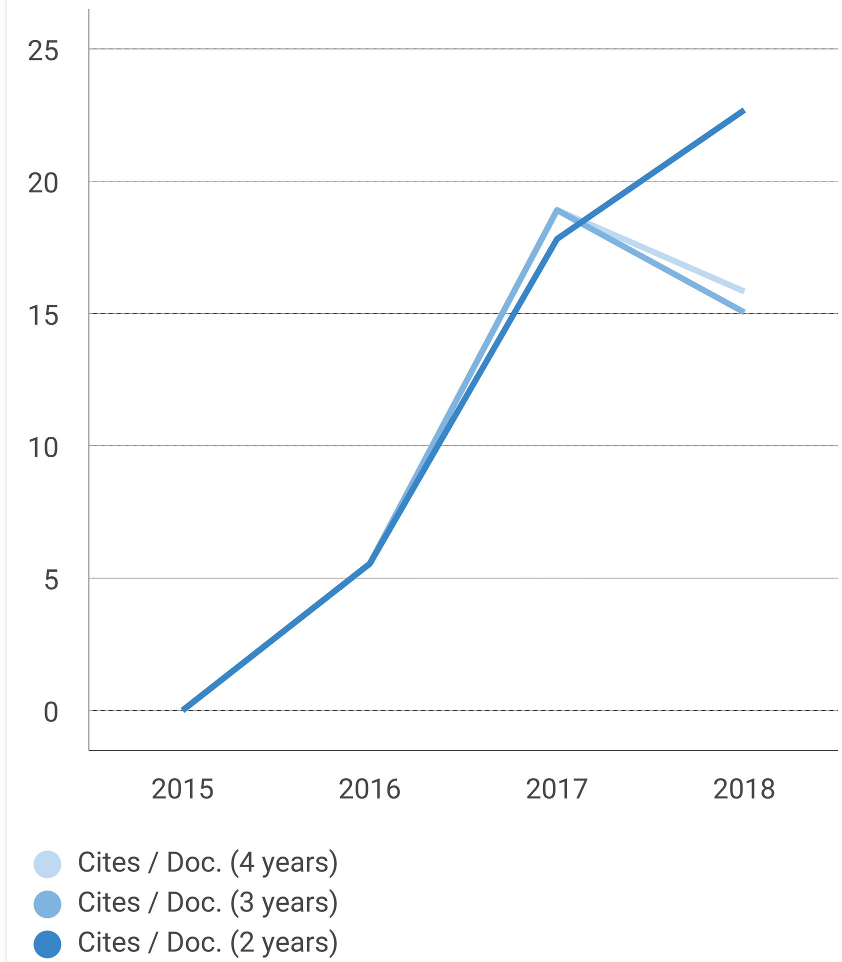

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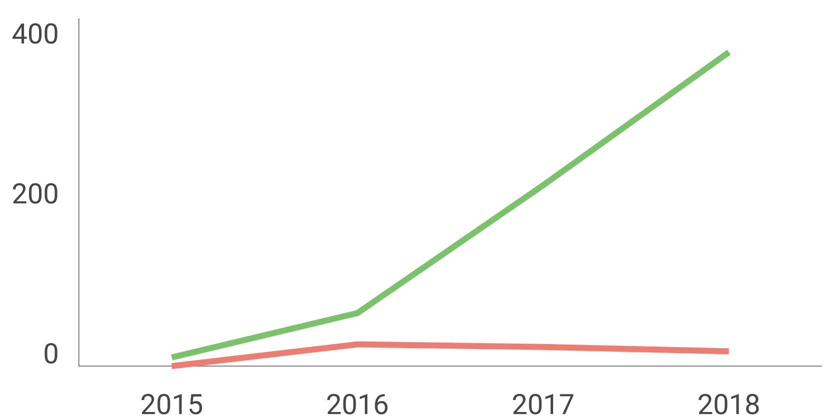

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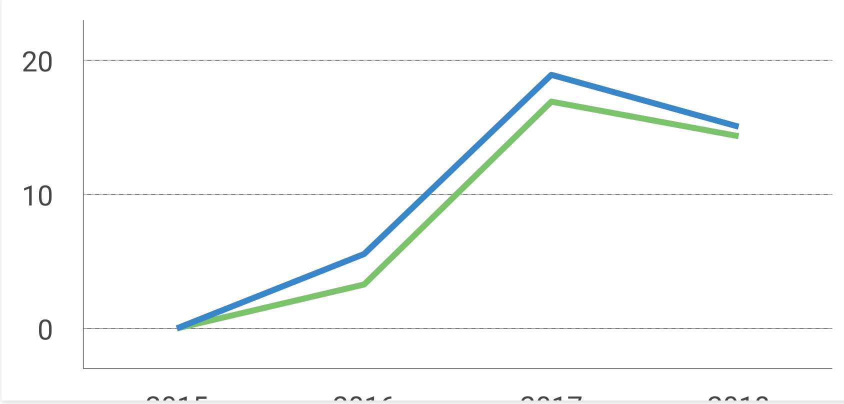

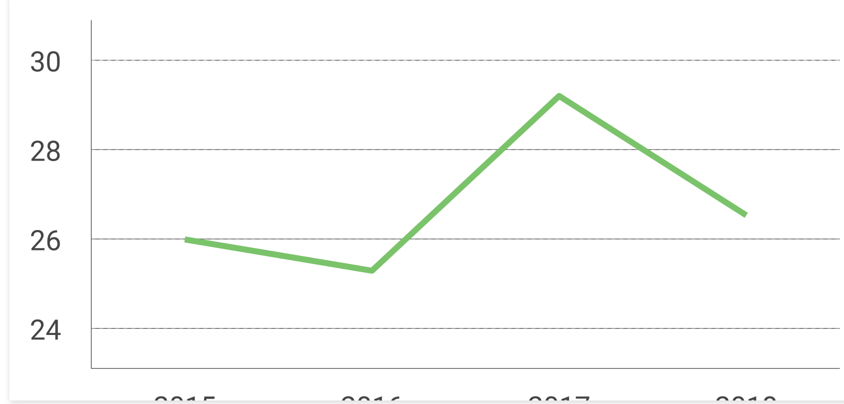

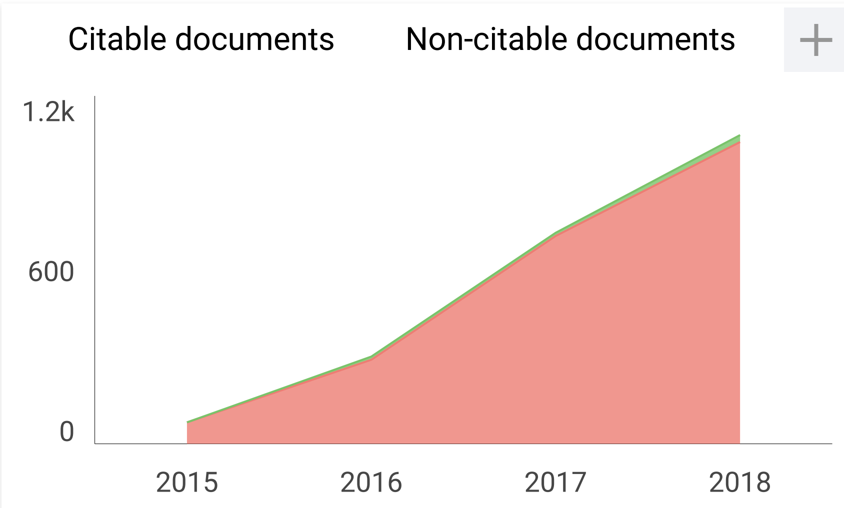

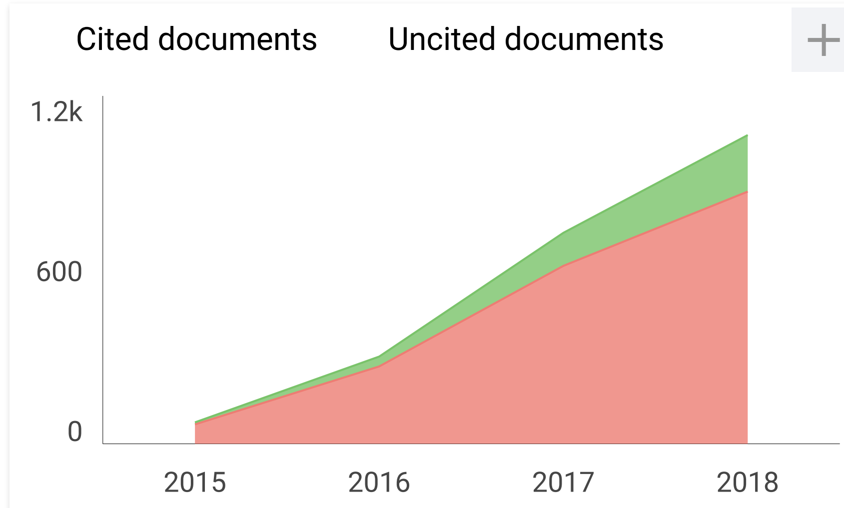

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Contents

A Fuzzy Inference System and Data Mining Toolkit for Agent-Based Simulation in NetLogo

Josue-Miguel Flores-Parra, Manuel Castañón-Puga, Carelia Gaxiola-Pacheco, Luis-Enrique Palafox-Maestre, Ricardo Rosales and Alfredo Tirado-Ramos

Abstract In machine learning, hybrid systems are methods that combine different computational techniques in modeling. NetLogo is a favorite tool used by scientists with limited ability as programmers who aim to leverage computer modeling via agent-oriented approaches. This paper introduces a novel modeling framework, JT2FIS NetLogo, a toolkit for integrating interval Type-2 fuzzy inference systems in agent-based models and simulations. An extension to NetLogo, it includes a set of tools oriented to data mining, configuration, and implementation of fuzzy inference systems that modeler used within an agent-based simulation. We discuss the advantages and disadvantages of integrating intelligent systems in agent-based simulations by leveraging the toolkit, and present potential areas of opportunity.

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1 Introduction

Agent-based simulation is an increasingly common approach for modeling complex phenomena using computational science to approach complexity [1, 2]. However, complex systems require realistic models to approach real problems. Consequently, novel tools for the modeling and simulation of complex problems, which may help modeling realistic models, are needed. Realistic models are not trivial to build, though, since new computational techniques for complex-systems are required to rethink the problem. One feasible approach is, e.g. to extend the functionality of currently available software tools, adding the new required functionality.

That is, many currently available software tools may offer mechanisms to add new features, providing an Application Programming Interface (API) to developers so they may build such extensions to the base application framework.

NetLogo is an accepted agent-oriented tool used mainly by social scientists with limited ability to program a computer [3]. Although the built-in models in NetLogo may be simple representations of complex problems, the available analysis is instrumental in demonstrating newly hidden behaviors. As a result, the tool offers a simulation engine that has been widely adopted for the computational modeling of social issues [4]. This tool offers attractive features of functionality, practicality, and user-friendliness, and has grown organically as user features are added by the community. Very importantly, it is available as freeware.

Prediction capabilities are important when dealing with simulation of complex systems [5]. Machine Learning (ML) is a computational method used to develop models and algorithms that allow for prediction. There are different ML techniques could be used for getting a model from real data, for example, association rule learning, artificial neural networks, clustering, and so forth. Furthermore, Hybrid Intelligent Systems (HIS) are a recent addition to the tool arsenal for modeling complex systems. They are methods that combine different computational intelligence techniques in modeling, including Artificial Intelligence (AI) and Machine Learning technologies. Neuro-fuzzy systems and evolutionary neural networks are prime examples of HIS.

In this paper, we present JT2FIS NetLogo; this is a Toolkit for Fuzzy Inference Systems (FIS) integration in agent-based models and simulations. FIS is a Hybrid Intelligent Systems that implements a Type-1 or Type-2 fuzzy system as a Machine Learning mechanism for prediction. This is a versatile tool with which a researcher could, for instance, use projection as a Decision-Making system in Agent-Based Modeling and Simulation.

The simplicity of use offered by NetLogo was part of the rationale for us to choose it as an appropriate platform in which to include fuzzy systems, and in particular the more innovative Type-2 Fuzzy Inference Systems (T2FIS) generation. Aside from providing this extended toolkit, we intend to show the usefulness of Type-2 Fuzzy Inference Systems in representing realistic social settings, as well as contribute to the improvement of available computational models.

Furthermore, in this paper we also discuss the advantages and disadvantages of integrating intelligent systems in agent-based simulations, and present some potential areas of opportunity and relevant applications.

1.1 Fuzzy Logic as a Methodology

The main contribution of Fuzzy Logic(FL) to this particular problem is a methodology for computing by using words [6]. One of our aims, in the narrow sense, is to show that fuzzy logic has well-developed formal foundations as a logic of imprecise (i.e. vague) propositions, and that most events that may be named "fuzzy inference" can be naturally understood as logical deductions [7].

Fuzzy Logic remains quite an active line of research [8]. According to Wan [9], its principal objective is to use fuzzy set theory for developing methods, concepts for representing and dealing knowledge expressed by natural language statements. A fuzzy system inference (FIS) is able, therefore, to understand the sum of a system of inference. A FIS is a rule-based classification method that uses fuzzy logic to map an input space into an output space.

FIS is based on three components: a rule base containing a set of fuzzy if-then rules, a database that defines the membership functions used in the rules, and a reasoning mechanism that performs the inference process consisting of applying the rules to achieve a specific result [10]. Mamdani FIS and Takagi-Sugeno FIS are types of inferences systems. Both have *IF-THEN* rules and the same antecedent structures. However, there are differences between them. Firstly, while the structure of the consequents for a Takagi-Sugeno FIS's rule is a function, in a Mamdani FIS's rule is a fuzzy set [11]. Secondly, defuzzification method is necessary for Mamdani FIS to obtain the crisp output because the output of a Mamdani FIS is a fuzzy set, whereas the output of a Takagi-Sugeno is a crisp value. Thirdly, the most significant difference in Takagi-Sugeno FIS is that it is computationally effective but loses linguistical interpretability for humans, whereas Mamdani FIS is intuitive and suitable to human interpretation [12].

Another useful concept is data mining that combines techniques from visualization, database, statistics, machine learning and recognition pattern methods with the objective of extracting and explain large volume of data. The primary goals of data mining are discovery, forecast and prediction of possible actions, with some factor of error per prediction [13]. Also, Data Mining helps to take decisions from identifying patterns, relationships and dependencies for generating predictive models [14].

Fuzzy C-Means (FCM) and Subtractive Clustering are also quite popular methodologies nowadays. Both of them can be used to extract patterns of data and create the initial configuration of an FIS. The Fuzzy C-Means algorithm (FCM) [15, 16] is basically the joining of c-means clustering algorithm with fuzzy data. This joining takes into account the data's uncertainty, helping prevent incorrect results and make correct crisp partitions [15].

A related methodology is that of Subtractive Clustering. It defines a cluster center based on the density of surrounding data [11], calculating the best choice of center based on mathematical approximations. The center data is determined by the distance of this data point from all other data points [17]; cluster center can represent a fuzzy rule of the system, and each found group represents the antecedent of this rule.

Finally, Agent-based modeling (ABM) is a simulation modeling technique which has greatly developed in last few years, e.g. in applications ranging from business to social problems [18]. ABM are commonly used to approach a complex system utilizing agents as main elements [19]. In ABM, problems are modeled through autonomous agents, capable of decision making. Each agent can evaluate its situation and make decisions by a set of rules. Further, agents have behaviors appropriate for the system they represent. These behaviors may also be based on interactions between agents, a main characteristic of agent-based modeling [18], where the agents interact with each other to simulate complex environments and predict emergent behavior [20].

1.2 Related Work

A popular methodology nowadays, we next mention a few representative examples of FIS in agent-based modeling. In [21], fuzzy sets are used in agent-based simulations to represent emotions and fuzzy rules in order to describe how some events are triggered by employing emotions, and how these emotions produce different behaviors. In [22, 23] the authors propose the use of fuzzy logic to formalize different types of personality traits for human behavior simulation. In [24, 25] the authors use fuzzy sets in the context of trust and reputation. In [26] the authors formalize various measures of success as fuzzy sets in a spatially iterated Prisoner's Dilemma, and explore the consequences. In [27] propose the use of fuzzy logic in Social Simulation to formalize concepts such as conflict, violence, and crime. In [28, 29] the authors incorporate the interpolation method in the decision making of their agents. In [30, 31] the authors explore discussion dynamics of competing products in different markets using agent-based models where various linguistic terms are formalized as fuzzy sets.

2 The JT2FIS NETLOGO Tool-Kit

The main idea behind the development of our JT2FIS NETLOGO toolkit framework is to help researchers implement Type-1 and Type-2 Fuzzy Inference Systems in NetLogo models, in particular where agents take decisions or express preferences through diffuse logic.

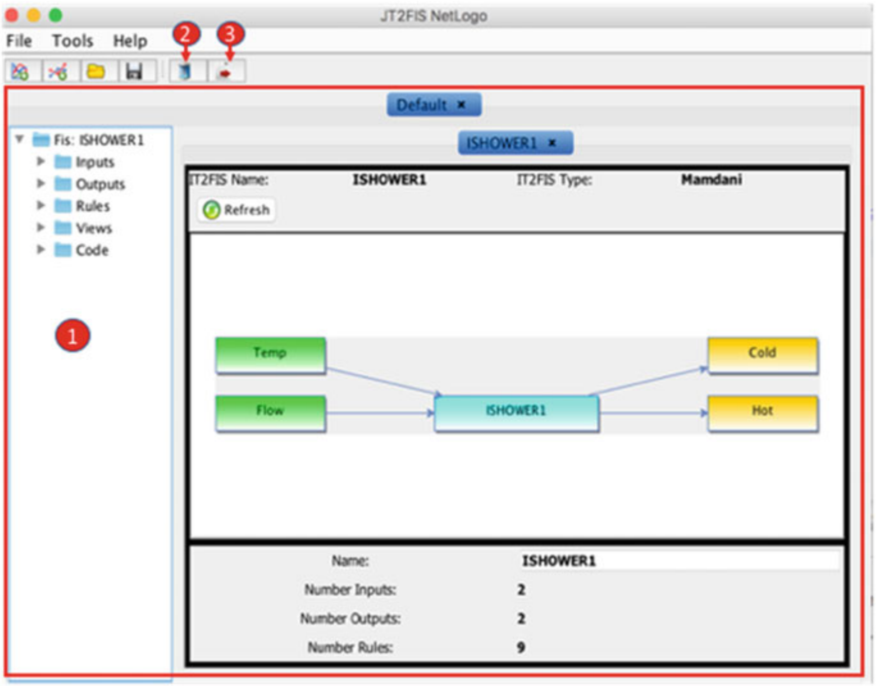

Fig. 1 Main elements for JT2FIS NETLOGO Tool-kit

The JT2FIS NETLOGO toolkit's architecture can be divide into three main elements (Fig. 1), as follows:

- Develop Mamdani and Takagi-Sugeno Fuzzy Logic System.
- Clustering.
- Export NetLogo.

2.1 Develop Mamdani and Takagi-Sugeno Fuzzy Logic System

The primary objective of this feature is to provide researchers with the integration of diffuse inference systems such as Mamdani and Takagi-Sugeno to their models. Also, it facilitates the visualization and configuration of the FIS to be able to include them in the simulations based on agents. The central core of this tool is basing on the JT2FIS library proposed in [32].

JT2FIS NETLOGO toolkit has five main modules for developing FIS:

1. Inputs.
2. Outputs.
3. Members Functions.
4. Rules.
5. Data Evaluation.

To explain how to create these fuzzy inference systems, we will use the ISHOWER example of Matlab.

2.1.1 Inputs

Using this module, we can add and manage the inputs (input linguistic variables values) of our diffuse inference system. The primary attributes of the inputs are the name of the variable and the limit of the values that can take (lower and upper limit). Figure 2 we show the Temperature entry for the ISHOWER example and its configuration (Name, upper and lower range, etc.) in addition to the membership functions that form it.

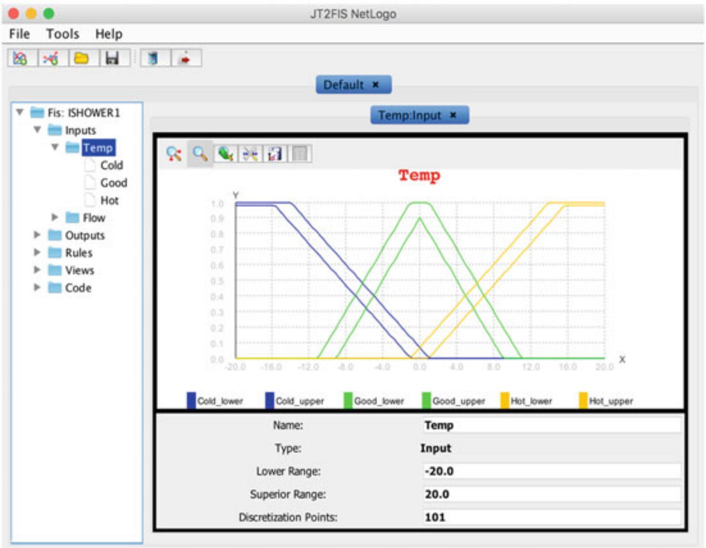

Fig. 2 Configuration of “Temp” input in “ISHOWER” example

2.1.2 Outputs

The output module allows us to add and modify the characteristics of the outputs (output linguistic variables values) of our FIS. As in the inputs, the principal attributes of the outputs are the name of the variable and its limit (lower and upper limit). Figure 3 we show the output "Cold" of the example ISHOWER and its configuration (Name, upper and lower ranger, etc.) in addition to the membership functions that compose it.

2.1.3 Members Functions

Membership functions are the linguistic values that an input or output linguistic variable can take. The membership functions used in our tool can see in [32]. In this module, you can add, delete and modify the attributes of membership functions as their name, parameters that compose it. Figure 4 shows the linguistic variable "Good" of the entry "Temp" of the example ISHOWER FIS this is of the triangular type with uncertainty in all the sides that compose it.

2.1.4 Rules

The rules are the basis of the knowledge of the diffuse Inference System. In this module, we can add, edit and delete these rules. This module shows us the inputs

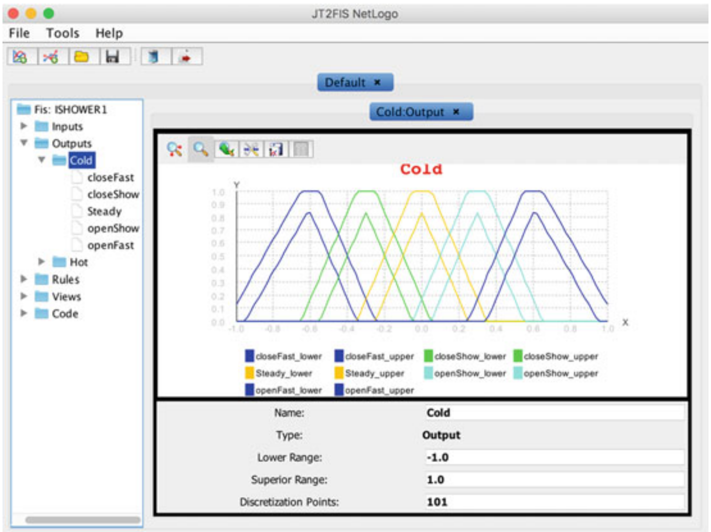

Fig. 3 Configuration of "Cold" output in "ISHOWER" example

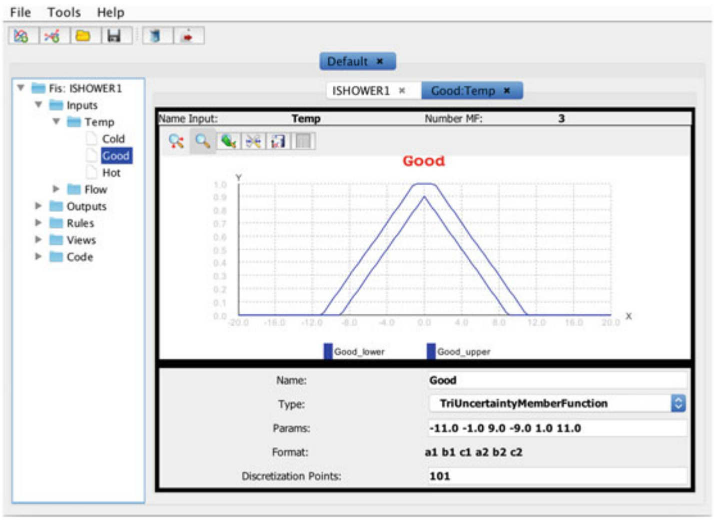

Fig. 4 Configuration of "Good" member function for "Temp" input in "ISHOWER" example

and outputs that make up the FIS; it is here where we must select the antecedents and consequents that make up each rule. The antecedents may be connected by the logical operators AND and OR. Figure 5 we can observe in more detail the formation of these rules.

2.1.5 Data Evaluation

Once the FIS configuration is complete, we can evaluate the data. When we talk about evaluating the data, we refer to giving numerical input values to its inputs. FIS through your system of knowledge (Rules) will provide us with the corresponding results for each of its outputs.

Figure 6 shows the FIS evaluation module. This module has different defuzzification methods; these methods are responsible for transforming the Fuzzy output to a numerical value. Also, this module offers other features such as configuration for methods implication, aggregation, and, or for inference.

We have two different options to select points to be evaluated. You can evaluate manually add points as shown in Fig. 7 or you can import a CSV file to evaluate a set of points automatically. The JT2FIS NETLOGO Tool-kit can export the results in CSV format.

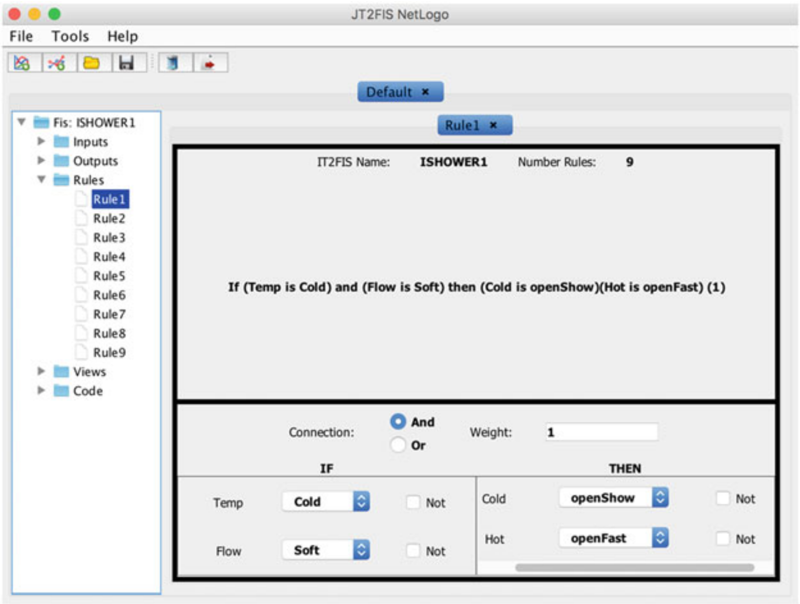

Fig. 5 Configuration of Rule 1 in "ISHOWER" example

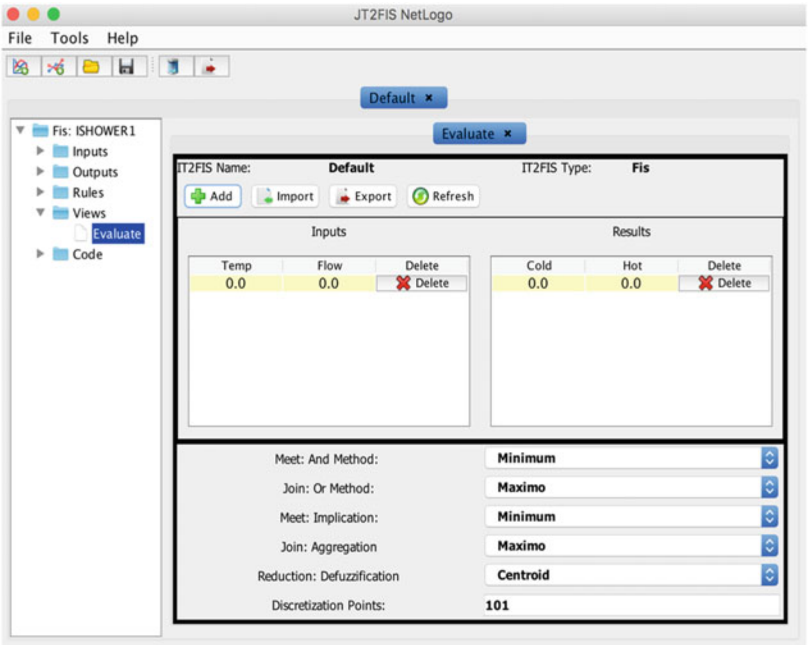

Fig. 6 Evaluate "ISHOWER" example

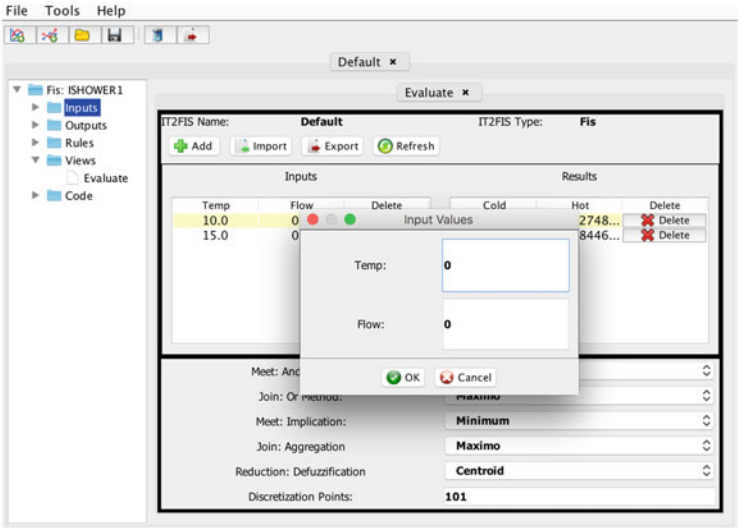

Fig. 7 Add point evaluate "ISHOWER" example

2.2 *Clustering*

The idea is to generate an FIS from CSV file through different clustering techniques. Figure 8 shows the graphic user interface of this panel. In this way, the user can set-up generation member functions and clustering method to apply the desired generation process.

Fuzzy c-Means is the default clustering method. In Table 1 list Type-2 member function available in JT2FIS NETLOGO Tool-kit.

2.3 *Export NetLogo*

For export the fuzzy inference systems generated, it is necessary to have the JT2FISNetLogo extension. JT2FISNetlogo is a NetLogo extension based on JT2FIS library. JT2FISNetlogo extension allows Fuzzy Inference Systems programming that can be accessible to non-specialists. The extension was built and tested on Version 5.3. The extension is available for educational purposes in [33].

The code generated for implementation of an FIS in NetLogo is saved in a file with extension .nls to be able to use it within any NetLogo model. Figure 9 shows an example of the generated code.

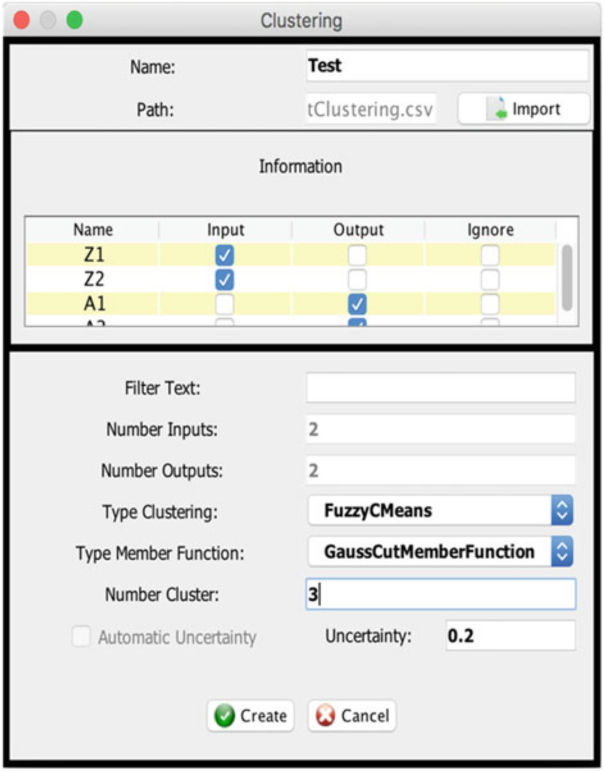

Fig. 8 Clustering panel user interface

Table 1 JT2FISCLUSTERING member functions

Type clustering	Type-2 member functions	Description
Fuzzy c-means	GaussCutMemberFunction	Params = [inputs outputs uncertainty]
Fuzzy c-means	GaussUncertaintyMeanMemberFunction	Params = [inputs outputs] Params = [inputs outputs uncertainty]
Fuzzy c-means	GaussUncertaintyStandardDesviationMemberFunction	Params = [inputs outputs] Params = [inputs outputs uncertainty]

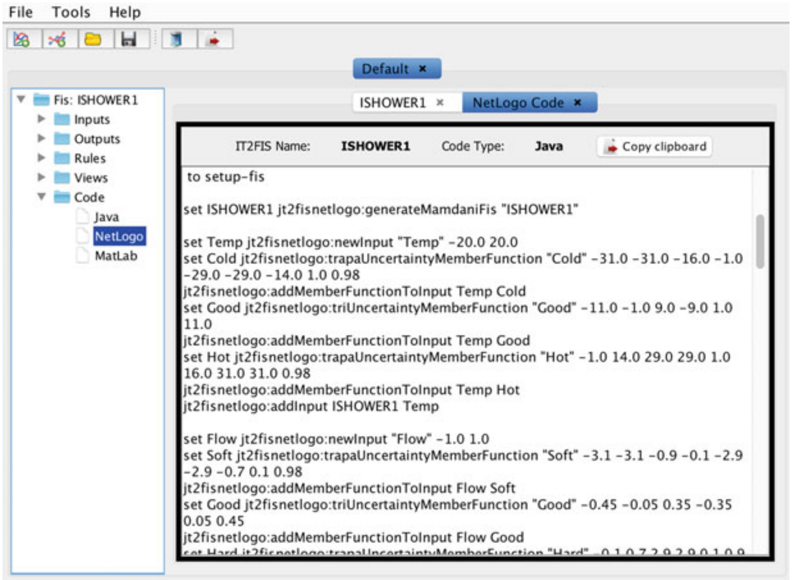

Fig. 9 NetLogo code generated in “ISHOWER” example

2.3.1 Executing FIS in NetLogo

To use JT2FISNetLogo extension, put the JT2FISNetLogo folder in the NetLogo extensions folder, or in the same directory as the model that will use the extension. At the top of the Code tab write: **extensions [jt2fisnetlogo]**.

The next step is to import the file with .nls extension. To import it is necessary to write down the previous line: **__includes[“pathFile.nls”]**.

Finally, we evaluate the FIS with the next fraction of code **set outputList jt2fisnetlogo:evaluateFisSingletonCentroid FIS inputList 101 0 0 0 0**.

Where the FIS variable contains the entire structure of fuzzy inference systems, the inputList variable is a list that includes the values for the FIS inputs that are required to make a decision.

Other variables are initial configurations that are not recommended to change to unless the researcher is familiar with the process of evaluation of the diffuse logic.

3 Use Cases

There are two different approaches to setting up a fuzzy system. The first consists of an empirical configuration and the second utilizes data mining processes to discover the values of membership functions and rules. In this section, we leverage two agent-based models from the NetLogo model library. Each model was added a FIS so that the agents had their diffuse concepts and their diffuse rules implemented. The objective is to illustrate a possible way of using diffuse inference systems in an agent-based model, with the help of the proposed tool.

3.1 Use Case 1: Empirical Configuration FIS

For this use case, we used the voting model included in the default NetLogo examples library [3]. In this example, we assume that the FIS is configured by a subject expert, using the proposed tool. This model simulates voting distribution through a cellular automaton, each patch decides for "vote," and this can change your "vote" taking into consideration of its eight neighbors.

The model plays the following rules:

- The SETUP button creates an approximately equal but random distribution of blue and green patches. In addition it performs the initial configuration of the FIS by calling the setup-fis method, the.nls file show this method.
- When both switches are off, the central patch changes its color to match the majority vote, but if there is a 4–4 tie, then it does not change.
- If the CHANGE-VOTE-IF-TIED? The switch is on, then in the case of a tie, the central patch will always change its vote.
- If the AWARD-CLOSE-CALLS-TO-LOSER? The switch is on, then if the result is 5–3, the central patch votes with the losing side instead of the winning side.

  The author suggests trying other voting rules, so we added the following rule:
- If the CHANGE-VOTE-BY-PREFERENCE? The switch is on; then the preference is evaluated using the FIS (Fuzzy Inference System), the central patch will change its vote depending on the preference depicted by the FIS. This rule consists of counting all blue preferences and green preferences. These are added to a list and passed as a parameter to the method jt2fisnetlogo: evaluateFisSingletonCentroid who is in charge of evaluating the decision to vote for the FIS configuration.

The FIS was empirically configured, with two inputs and one output. The inputs of the system are BlueVotes and GreenVotes, and the output is BluePreference. The inputs are transformed from crisp data to linguistic values LowBlueVotes, HighBlueVotes, LowGreenVotes, HighGreenVotes by the fuzzify method, then the corresponding output linguistic value is inferred by the inference system, to finally de-fuzzify is applied to get a crisp output data. Figure 10 shows the structure of the FIS for this particular case study.

The FIS represents the preference of all voters that is described by functions membership and rules into the system. The fuzzy system implements the following rules:

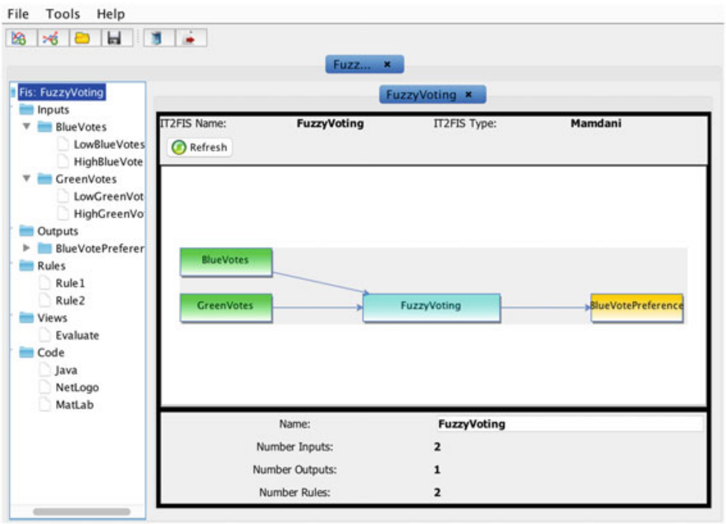

Fig. 10 Fuzzy inference system generated for voting model

- Rule 1: LowBlueVotes and HighGreenVotes then Low-BluePreference.
- Rule 2: HighBlueVotes and LowGreenVotes then HighBluePreference.

Figure 11 shows the results of the model after adding the new rule and executing the simulation.

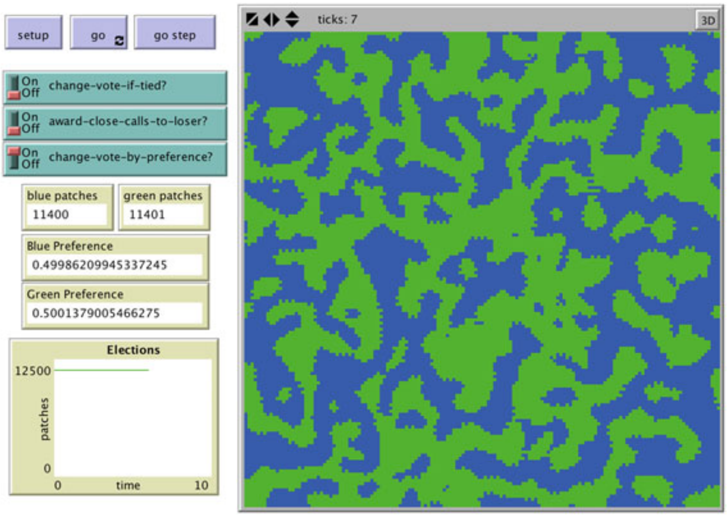

Fig. 11 Case study "Voting Model" implementation in NetLogo screenshot capture

3.2 Use Case 2: Data Mining Configuration FIS

For this use case, we model religious segregation in city of Tijuana. Tijuana is a border city in the northeast of Mexico. Tijuana is a city that has overgrown in recent years as a product of migration. As a consequence, this city has a great diversity of cultures, traditions, and religions [34].

Instituto Nacional de Estadistica y Geografia (INEGI) has provided us with the necessary data for this case study. INEGI is a federal government organization responsible for collecting economic, geographic and socio-demographic data [35]. For our case study, we have considered two different locations.[1] We take into account the 2010 population census in Mexico [35] to select the variables of our model. These variables show below:

1. P15YMAS = Population over 15 years old.
2. P15YMSE = Population over 15 years old without education.
3. GRAPROES = Education.
4. PEA = Working population.
5. PEINAC = Non-working population.
6. PCATOLICA = Catholic population.
7. PNCATOLICA = Non-catholic population.

The next step is to take the data and submit it to a process of data mining, the method chosen was FuzzyCMeans method. We select variables 1–5 as inputs and variables 6–7 outputs. This process can observe in Fig. 12. With the FuzzyCMeans method, we construct a System of Inferential Fuzzy for the Location 187 and 293 for both cases we select 3 clusters. The Fig. 13 show the FIS Location 187 obtained.

After that, we include the FIS generated in the NetLogo Segregation Model. This FIS determines whether an agent is catholic or non-catholic. If the agents do not have enough neighbors of the same religion preference, they move to a nearby patch. To distinguish religious preference, we use a red color for Catholics and green for non-Catholics. The model has the following rules:

- The SETUP button create the initial configuration of the FIS by calling the setup-fis method, this method is found in the.nls file. Choose the religious preference of each agent, red for Catholics and green for non-Catholics. The FIS calculated the religious preference. The values for FIS inputs are calculated randomly.
- DENSITY slider controls the occupancy density of the neighborhood (and thus the total number of agents).
- The %-SIMILAR-WANTED slider controls the percentage of same-color agents that each agent wants among its neighbors. For example, if the slider is \%set at 30, each green agent wants at least 30\% of its neighbors to be green agents.

[1]Locations are the terminology used to describe wide geographic areas of the city that are composed of Basic Geo-Statistic Area (BGSA).

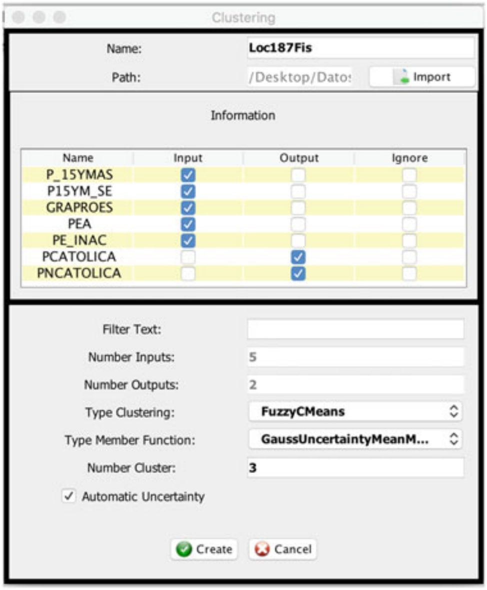

Fig. 12 Screen printing of the clustering process for location 187

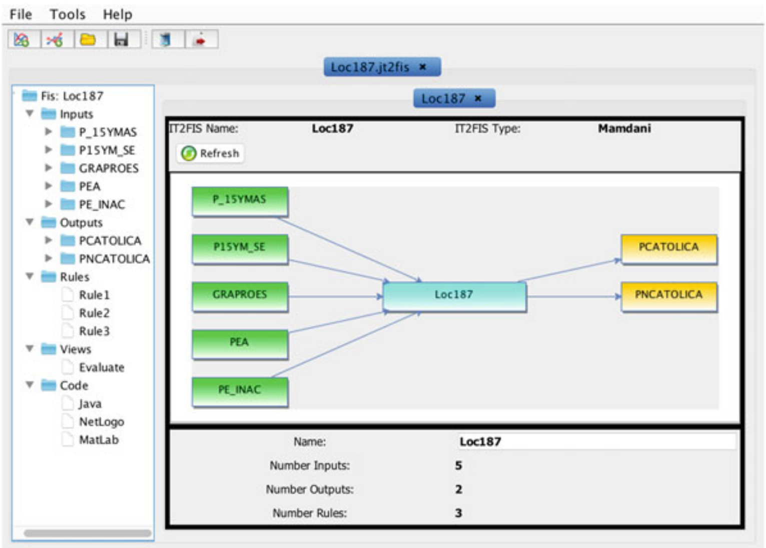

Fig. 13 Fuzzy inference system generated for location 187

- The % SIMILAR monitor shows the average percentage of same-color neighbors for each agent.
- The NUM-UNHAPPY monitor shows the number of unhappy agents, and the % UNHAPPY monitor shows the percent of agents that have fewer same-%color neighbors than they want (and thus want to move). The % SIMILAR and the NUM-UNHAPPY monitors are also plotted.

The importance of creating an FIS with some method of grouping extracting the rules and their configuration of the data is that it becomes a model more attached to the reality. You can also observe the preferences of a population at different levels, either at the level of a locality, colony, country. We use two different simulations, one for location 187 and one for location 283. The Figs. 14 and 15 show the results

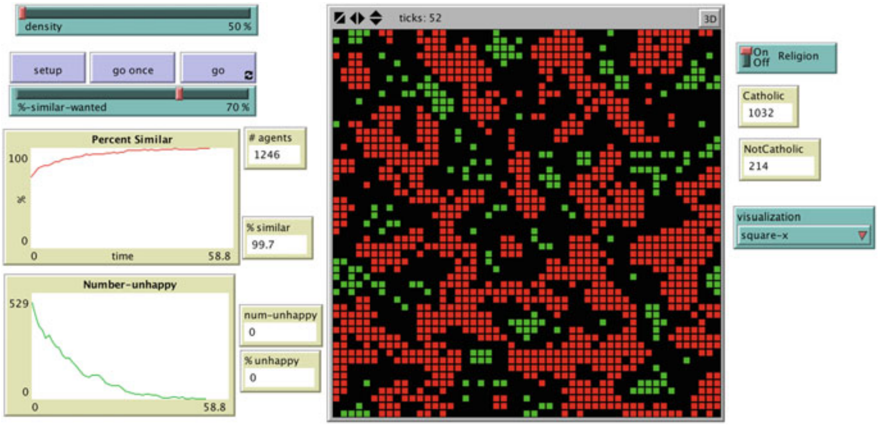

Fig. 14 Religious segregation simulation for location 187

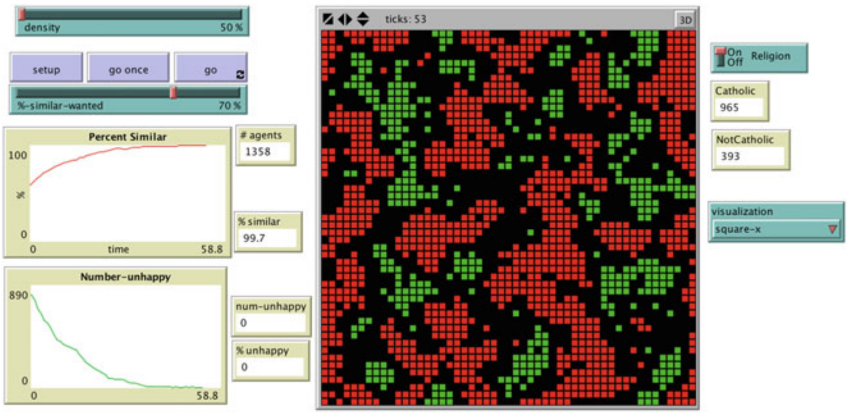

Fig. 15 Religious segregation simulation for location 283

of these simulations. We can see that locality 187 has a greater preference for the Catholic religion than the locality 283.

4 Discussion and Applications

We have leveraged our application to illustrate how to build an FIS from user modeling actions, directly on the visual application, as well as by data mining from real data.

In the first use case, the user must know how to build the FIS configuration step by step, in order to get the desired system. The system will use the experience of the modeler and provide consistent outputs. This kind of system may be the most convenient example for starting to build simple decision-making systems that can be built upon. The advantage is that the modeler can assume all de rules and values and build the system theoretically, so to explore its impact into the full model. The disadvantages are that the modeler must know the purpose of member functions, rules, fuzzify and defuzzify FIS mechanisms, and their meaning in the model.

In the second use case, the user not necessarily must know how to build the FIS, but he can discover the rules and configurations representing hidden information by data mining real data. The system will represent knowledge discovered from the system and will provide consistent outputs with the data, but not necessarily as expected by the modeler. This kind of system could be interesting to add complexity and therefore improve an existing decision-making system. The advantage is that the modeler can discover all de rules and values and build the system realistically to reproduce the result of it into the full model. The disadvantages are that the user depends heavily on the original data (the data must adequately gather and formatted conveniently by the researcher), and the discovered member functions and rules could become complex and therefore difficult to understand by the modeler (the meaning of they into the model could be confused if there are a lot of rules or member functions discovered).

In either case, the modeler can export each generated configuration to the NetLogo model, and build the obtained system by programming, leveraging the extension. The focus can then be shifted to incorporate the FIS, e.g. as a decision-making system, to produce an imitative simulation, without having to worry about member functions, rules, fuzzify and defuzzify FIS mechanisms.

4.1 From Simplistic to Realistic Model

Most of the agents-based simulations are simple agent-based designs that model features from a traditional point of view. Researchers use models to create a standard or example for comparing the study case features in different scenarios. A model could be a representation to show the structure or behavior of an interesting phenomena, e.g. to describe the observable activity in humans, or the aggregate of responses to internal and external stimuli. Sometimes, they use to set up behavior proceeding or derived from reason or based on reasoning programmed by the modeler, many times characterizing a process of selection in which each item of a set has an equal probability of being chosen.

However, models currently require the description of behavior depending upon experience or observation, not necessary using the scientific method or clearly set theory. Moreover, the knowledge communicated or received concerning a particular fact or circumstance should be considered different (unlike or incongruous) or composed of parts of different kinds; having widely dissimilar elements or constituents, rather than same kind or nature. We expect future models based on explanatory reasoning to generate or justify hypotheses, helping inference to the best explanation as a methodology. Realistic models should help researchers in the discovery process, suggesting a new hypothesis that follows a distinctive logical pattern, as a result of computing, rather than both inductive logic and the logic of hypothetical-deductive reasoning.

4.2 Fuzziness and Uncertainty in Agent Behavior

Uncertainty and fuzziness are two critical concepts for representing agent behavior in a given environment. Fuzziness is a central component of behavior, since realistic setting decisions made by the use of heuristics may not represent results from clear rules. However, alternative and possibly competing heuristics are evaluated regularly, potentially leading to significantly different outcomes under relatively similar situations. We may therefore say that decision making in a fuzzy system represents a relative and contextual endeavor, with agents that consider what they perceive and what they know, with an ubiquitous feeling of uncertainty. Because agents always consider some degree of uncertainty perception and knowledge when making decisions, the fuzziness of the system introduces a level of uncertainty to the final choice. Therefore, we can say that the process of decision making for an agent is not only a fuzzy system, but rather a compatibility threshold between what the agents sense and their knowledge, itself also fuzzy.

There continues to be an active discussion in the literature concerning the degrees of uncertainty in a fuzzy system. In the meantime, we can assume that degrees of uncertainty allow us to represent the level of influence that different levels of reality, as expressed in the simulation, especially since agents interact in a social network. We can thus represent agents that qualify the dispersion (or fuzziness) of the data generated by these interactions as contained intrinsically, with corresponding perceptions that can vary, and thus are modeled individually.

4.3 Opportunity Areas for FISs Applications

We identified some opportunities areas where we consider that researchers could use a FIS. For instance, FIS can be utilized mainly as a system able to evaluate a set of inputs with a complex non-linear function for description or prediction. The FIS could represent an environmental multi-variable aspect of the system for example but could be utilized as a Decision-Making System into an agent besides.

Information and communication technologies. In ICT research and technology, FIS could be used as a system profiler, able to evaluate different aspects of users for classification.

Socio-ecological systems. In social sciences modeling, FIS could be utilized as a Decision-Making Systems using agents to describe how individuals made decisions from multiple and complex social, as well as environmental stimuli.

Biological and (bio)medical complexity. In health sciences modeling, FIS could be utilized as a prediction function in disease propagation to risk and contingency management.

Infrastructure, planning, and environment. In urban planning and public policy modeling, FIS could be used as an institution or organization decision-making system that evaluate actions according to a set of public policies and environmental values, e.g. in infrastructure planning [36, 37].

Economics and finance. In businesses and financial modeling, FIS could be used as a system able to evaluate different aspects of complex multi-variable systems to predict prices and market changes.

Cognition and Linguistics. In knowledge management modeling, FIS could be used as a communication/interpretation system able to allow for word-based computation.

5 Conclusions and Future Work

In this work, we demonstrate how to include Type-1 and Type-2 Fuzzy Inference Systems and Data Mining for Agent-Based Simulation in NetLogo. As an application use case, we modified the segregation model and voting model provided in NetLogo example library to show how to develop fuzzy inference systems in NetLogo.

We use the voting model for exemplifying how to use uncertainty and perception on agent-based simulation. The toolkit can apply for developing decision-making system, where individuals choose to donate to a charitable cause, or rent or buy a home. Furthermore, we use the segregation model allows us to exemplify how to use data mining algorithms for discovering the member functions and rules to develop an FIS from a data set. The toolkit introduces in this paper show how to use a real data set for developing a decision system in which individuals decide on whether to Catholic or not Catholic groups preference.

With this toolkit, the researcher can create, discover, explore, and import into NetLogo a Type-1 or Type-2 Fuzzy Inference System using a NetLogo extension to incorporate a machine-learning system as a decision-making system into simulations. FIS can be used to describe of complex systems or for predict systems response to add a decision-making system to agents.

Moreover, a FIS is a Hybrid Intelligent Systems if it could be generated from real data set using clustering algorithms, and it can be used to describe complex systems and predict systems response, adding complexity to an agent's decision-making. This tool provides a least two well-known clustering methods, fuzzy c-means, and subtractive algorithms, in order to produce a Mamdani or Sugeno Type-1 or Type-2 Fuzzy Inference Machine respectively.

Our future work is to upgrade the extension to work properly in the new version NetLogo. We are developing clustering methods to incorporate in the latest version of our toolkit and improve the extraction of the FIS. Our next step is to include neuro-diffuse systems in our tool. With this new feature, we can improve the behavior of agents, since they can add, modify or delete rules in their behavior in a dynamic way. We goal for the future is creating a software agent smart enough for modeling realistic human actors in decision-making systems.

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