Fuzz in a Row

Application of Fuzzy Logic for a Discrete Decision Tree

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Abstract

In order to test application of fuzzy logic in discrete decision problems an Artificial agent was created in this experiment to play the game of Connect-4 using a type-I fuzzy controller. The parameters in the controller were first decided on expert knowledge and then in a separate version, also learned from generated data of another Connect-4 AI. The fuzzy agent was then tested against an agent based on Monte Carlos search and a brute force calculating agent. What was found is that the data based agents rules had a too low firing strength, resulting in poor performance of the fuzzy agent. The expert knowledge based version however, performed average-good.

1. Introduction

Applications of fuzzy logic can be found within many fields of research. They are usually used for continuous variables, yet not an adequate amount of research has been done on the application of fuzzy logic in discrete problem settings (Pang, Wang, Zhou & Dong, 2004). In order to experiment with this, fuzzy logic will be applied in this paper to a discrete decision problem: the game of "Connect-4".

Games lend themselves well as testbed for AI applications. They form a simulation in which, unlike the real world, the inputs and outputs are easily distinguishable from noise and the expected behavior is easily evaluated. This is not an unfamiliar idea, "Computational Intelligence methods have been employed to computer games since they provide dynamic and challenging elements that are similar to real world problems" according to Sahin and Kumbasar (2017). Yet it was never tried on a discrete game such as this. Thereupon an AI agent was developed in this paper using type-I fuzzy logic to play the game of Connect-4.

1.1 The game

Connect-4 is a game played by 2 players, let's name them "1" and "2". The game sets itself around a 2 dimensional board, with a discrete number of slots. In a turn, first player 1 gets to do a move, and subsequently player 2. In a move, a player chooses a column of the board where it will place its chip. The chip will be placed on the bottom of that column given that there is not a chip in that particular slot yet. Otherwise, it will be placed on top of the already occupied slots in the respective column.

The game ends when either the board is full (a draw) or a victorious situation is reached by one of the players. The players can do so by placing four chips abreast (connecting) in either vertical, horizontal or diagonal way.

1.2 Literature Review

Pirovano and Lanzi (2014) wrote about a scripting game called "Fuzzy Tactics" in which a player chooses the strategy by natural language rules similar to the ones often seen in a fuzzy controller. Thereafter a fuzzy controller maps crisp inputs to crisp outputs during the game. This is done relatively much in game development because of the effectiveness of it (Pirovano & Lanzi, 2014). The fuzzy connect-4 agent will be designed likewise.

What makes Connect-4 different however is the simple decision tree. The tree can be seen as a multi-agent game. Arfi wrote on how to use fuzzy logic in game theory. He describes a method of fuzzy domination of action, fuzzy Nash equilibria and fuzzy strategies. These concepts incorporate uncertainty about the opponents move (Arfi, 2006). The way to handle a strategic game is similar to a decision tree and therefore "fuzzy strategy" lays an foundation for a fuzzy agent maneuvering the tree.

Moreover, Allis wrote in 1988 that Connect-4 is solved for the standard board. The search tree can become very large, but it is solved in favor of player 1 (mathematically). If both play perfect, player 1 can always win. The best player 2 can do is draw. One of the reasons why is because of the number of

columns (7), by playing in the middle at the first move, player 1 can guarantee player 2 will never obtain a row-victory (Allis, 1988).

2. Methods

2.1 System and tools

The system used was a HP EliteBook 8570w with an 2014 intel i7 processor. The agent was implemented in Python 2.7 (including but not limited to: Numpy, Scipy, SKlearn and SKfuzzy).

2.2 Setup

2.2.1 The experiment

In this paper an experiment was performed to play the game of Connect-4 with an AI based on a fuzzy-controller. To evaluate the performance of this agent, it has been tested in a competition against two other AI players. The first is based on Simple Monte Carlos Search, an underdeveloped version of the algorithm that was used for the famous alpha Go (Silver et al., 2016). The second opponent uses a Brute-Force based approach. By examining the results of games from the fuzzy agent against these two opponents, conclusions can be drawn concerning the performance of the fuzzy agent. Because both the fuzzy agent and the brute force agent are deterministic we only need to play 2 games to evaluate them (one for each player starting the game). For the matches against Monte Carlos the game has been played 80 times.

Opponent specification:

The variation on the Monte Carlos algorithm in this paper first collects all the possible moves it can make at that moment in the game. Then, for each possible move it takes 0.8 seconds to evaluate that move. The evaluation goes as follows: it plays out as much games as it can within the given time limit, by just playing random moves. If it reaches an end situation it adds 1, 0 or -1 to a counter (won, tie, lose). This way it takes a random sample (usually ranging between 800 and 1200 samples) of the quality of that move. The on average best scoring move gets chosen

The brute Force based algorithm also collects all the possible moves, and consequently it will simply play 3 moves in any way possible and see how many of those moves lead to a victory in 1 turn, how many in 2 turns and how many in 3 turns. It then assigns a score to those numbers: 64,8,1 respectively. The best scoring move gets chosen.

2.2.3 The board

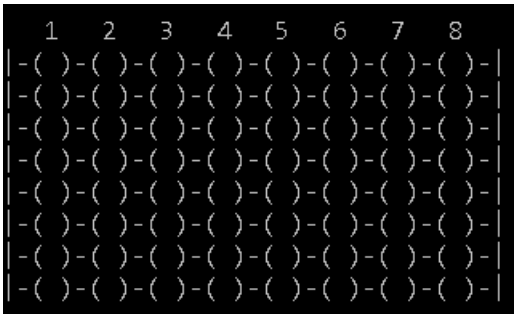

Figure 1:
The board used in the experiment

Traditionally Connect-4 is played on a board with dimensions 7 times 6 (height and width respectively). This game however is already solved. The first player always wins if he/she plays perfectly (Allis, 1988). This is why the playing field in this game is expanded to an even amount of columns and an higher amount of rows: 8x8. See figure 1 for an example of an empty board.

Now that the opponents, board and scope of the experiment are defined, the fuzzy agent can be introduced. From here on the fuzzy agent will be referred to as the agent.

2.3 What's the Fuzz?

Unlike Boolean logic, fuzzy logic allows expressions and usage of vagueness and uncertainty. There is a variety of occasions where that is especially useful. Yet a game such as Connect-4 does not have a lot uncertainty in it, at least not in the conventional fuzzy logic way. It is a discrete game, based on a decision tree with a limited amount of choices in each node. There is no column 6.4 or 3.2 for example and it would not be logical round them up or down because the output in columns is not continues nor linear. For example: in a particular state in the game column 5 might be an excellent move, 6 a horrible one and 7 relatively good again. The score of one column does not imply anything about its neighboring column. If the columns would be the crisp output of the system that would a problem, because there is no clear range.

Instead, the agent will use fuzzy logic on evaluating the moves that are available. In fuzzy logics we can evaluate uncertainties we have about certain states of variables. Is the water out of the warm faucet hot? It is not true or false. It might be "slightly hot", and "barely cold". The same principle will be applied to the fuzzy agent. If I choose to place my chip in column 6, is my new state better, amazingly better or slightly worse (etc.)? The linguistic approach will guide the agent through the vagueness of evaluating and choosing a move, by letting it choose move that got the best grade from a fuzzy controller.

2.4 Variables

To evaluate however, we need a crisp input. The agent will do so by counting for certain patterns in the board. These are patterns based on the brute force agents evaluating system, which indicate improvement for the agent. The count of the following patterns will form the crisp input for the fuzzy controller:

2.4.1 input variables

Firstly, there is the “Potentials”. These are single moves with enough space around them to eventually make a connect-4. An example of a board(4x1) with potentials(board) = 1:

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Secondly, there is the “Win-In-2’s”. This is the amount of possibilities that could lead to a victorious situation within 2 moves. An example of a board(5x1) with Win-In-2(board) = 2:

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Thirdly, there is the “Win-In-1’s”. This is the amount of possibilities that could lead to a victorious situation within 1 move. An example of a board(1x4) with Win-In-1(board) = 1:

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Finally, there is the “Progression”. This is the amount of turns that have been played so far. This feature is added because it is desirable that the agent strives for a victorious situation as soon as possible.

Because the game lasts multiple turns, we can reuse the first three input variables mentioned above from previous turns. In the most extreme case this would lead to 3x64=192 variables. That is a bit much however, but fuzzy agent 2 and 3 will look two turns back for input (fuzzy agent 2 and 3 will be defined later in the paper*). Adding progression to that number leaves us with 3x3+1 = 10 input variables. This way the agent can also keep track of improvement in its situation, not just the absolute state at that moment.

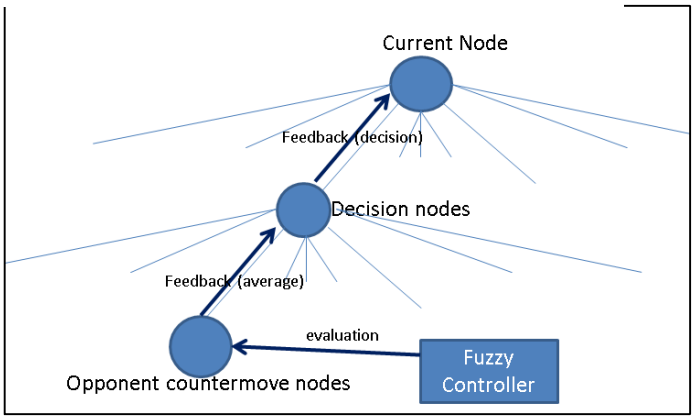
2.4.2 output variable

The output of the fuzzy logic controller is a grade between -1 and 11, describing the quality of the state of the game in which the evaluation took place. Range <0,10> is used for regular turns, yet <-1,0> and <10,11> only for indicating a win or a loss.

2.5 Algorithm

In the initialization of each turn, the agent will collect its possible moves (decision nodes), then collect all the child-nodes in which the opponent makes a countermove (see figure 2). In these child-nodes the agent will gather crisp input variables and do fuzzy evaluation. Consequently the agent will take the average of the evaluation in the child-nodes

Figure 2: Illustration of the algorithm



(countermoves), and assign that average to their parent node (decision nodes). Then the move out of the decision layer with the highest average is chosen. See figure 2 for an illustration of a decision made in every turn

The fuzzy system is of a Mamdani type and uses the min-and method, the product-implication method and the centroid-deffuzification method.

*Three different versions of the fuzzy agent have been implemented. One based on “expert knowledge” (fuzzy agent 1 : appendix B.1), one based on learning data from the brute force agent (fuzzy agent 2: appendix B.2) and the third (fuzzy agent 3 : appendix B.2) is also based on the same data but has an simple extra defense mechanism which can be summarized as: *if any of the counter moves of the opponent leads to a loss, don’t choose the decision node that leaded you there*.

Agent 2 and 3 have the full 10 inputs as described in section 2.4.1, whilst agent 1 takes in only progression, current-win-in-1 and current-win-in-2, resulting in 3 input variables. From this point the paper will be referring to agent 2 and 3, as it will not continue on agent 1.

2.6 Learning

2.6.1 Training data

In order to increase the agents accuracy data learning was applied. First, the dataset was created out of the evaluation method of the brute force agent. This agent was chosen as an example because it performed relatively well against humans and it was easy to apply on the fuzzy agent since similar input variables are used. 500 games were played in which two random agents played each other, aimlessly choosing a random move every turn (random walk). The brute force agent would evaluate every move in between and assign it a score. The total score was then scaled between -1 and 11. This resulted in a dataset of 11,379 data points. Consequently membership learning could be done and finally rule learning.

2.6.2 Learning memberships

The first step in learning membership is plotting out each feature against the scoring vector and analyzing how many clusters could be identified (on intuition). Thereafter, the feature and output were fed to the C-means (Dunn, 1973) clustering algorithm (using factor m=2.6). The algorithm outputs the cluster-centroids and memberships of data points to those clusters in the feature-output space. Next, a 3-dimensional result space can be defined: the feature-output-membership space. Following, we project the output-axis onto the feature-axis and that leaves us with a membership-feature space. This is a space on which we can then fit a Gaussian membership function for each cluster. The standard deviations and centers of these Gaussians will define the membership functions for our input variables.

2.6.3 Learning Rules

After learning the memberships, the fuzzy rules can be determined. The agent uses Wang and Mendels (1992) rule learning technique. After applying the cleanup of the rules as in step 3 and 4 in Wang and Mendel, only 127 of the 11,379 rules remain.

2.6.4 Manual adjustment

Some manual adjustments have been done because it seemed that no rule would ever have a firing strength over 1e-17, so the (work around) solution was to increase the standard deviation of all memberships with a factor 10 and add 10 as well. This is done after file reading, all the membership parameters stated in appendix B are before manual adjustment.

3. Results

Figure 3: Result of competition. Cells indicate the victories/losses for the fuzzy agent

Fuzzy Agent starts	**Monte Carlos**	**Brute Force**
Fuzzy agent 1	8.75%	won
Fuzzy agent 2	0%	lost
Fuzzy agent 3	0%	lost
Opponent starts	**Monte Carlos**	**Brute Force**
Fuzzy agent 1	12.5%	won
Fuzzy agent 2	0%	lost
Fuzzy agent 3	3.75%	won

As can be seen in figure 3; agent 1 outperforms the brute force agent and the other fuzzy agents. The agent based on Monte Carlos search algorithm is the best agent in the competition. Remarkably, all fuzzy agents score either worse or equally good when they start the game than when they do not.

Agent 2 is the worst performing version of the fuzzy agents. When analyzing it play, it seems to do well in the offense but does not care for defense. For example, when the opponent has three disks in a row and agent 2 has two, it prefers to go for own gain and expand its own 2 in a row to 3 in a row, rather than blocking the opponent and avoiding a loss. Because of this seemingly selfish (and ignorant) behavior a simple defensive method needed to be added. Thus agent 3 was created, who performed slightly better.

Fuzzy agent 1 is relatively quick (roughly 5 seconds) in evaluating, but also agent 2 and 3 do not take that long (roughly 14 seconds).

3.1 Learning

All variables were successfully trainable by the data. Most resulted in usable membership functions. See figure 4 for an example: Win-In-2, or Appendix A for the other variables. Some had a few useless membership functions in them with a very low standard variation, which were removed manually.

Additionally, rule generation also worked. A problem however was that because the large number of rules and variables, the firing strength stayed too low for the software to pick up on it. Hence the standard deviation of all membership functions needed to be raised manually in order for it to still work.

3.2 Conclusion

The agents with rule learning performed worse than anything else (including agent 1), showing that either the specific dataset is not functional for this purpose or data learning is not the method for making an agent for a game with a discrete decision tree.

Furthermore, the agent with defense mechanism did win some games. This showed that the technique does work, but far from optimally.

There is however no clear conclusion to be drawn of the results of that agent. The need of addition of defense mechanism and barely firing rules pointed one way. Yet it did seem to work for offense, pointing the other. This leaves a mixed message.

Nonetheless, the results of agent 1 do indicate a strength of expert knowledge based fuzzy logic in decision tree games.

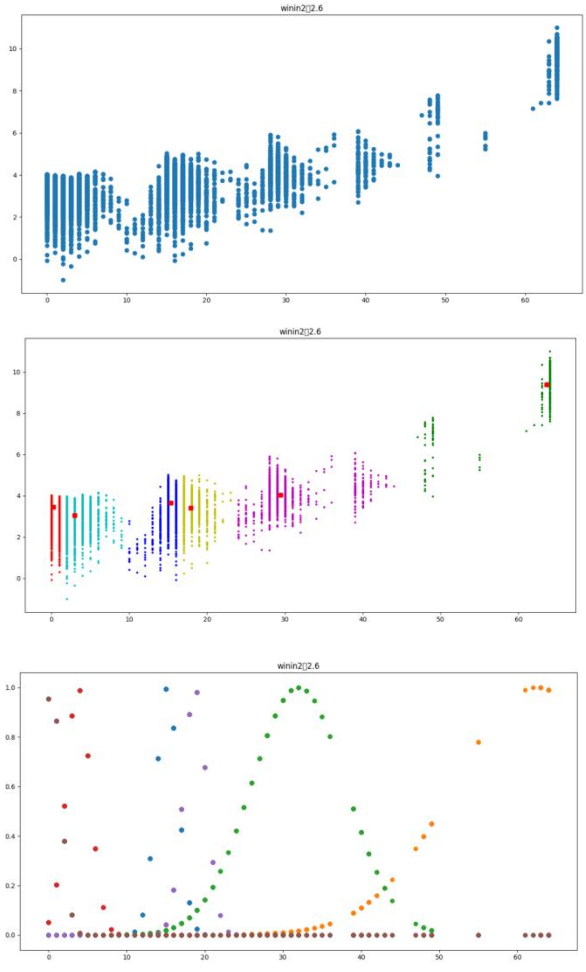


Figure 4: Learning membership of win-in-2 variable (see other variables in appendix B) a) raw data, b) clustering result, c) result of learning membership functions

4. Discussion

There are multiple reasons why the fuzzy agents based on the dataset are not performing as well as expected. The first is that perhaps, even though the process of fitting memberships was succeeding, the dataset was not right for this AI. It is after all a dataset produced for the sole purpose of using it, and design biases could have been the pitfall. It could even be that certain situations, who did appear in the dataset, just do not happen in the real game, resulting in faulty rules that would never fully fire. This could be the case because the dataset was created by doing random moves. A new possible approach could be to evaluate the fuzzy system on how many errors it makes to the perfect strategy of the game according VICTOR (Allis, 1988). The dataset could be evaluated with this scoring, and parameters of the fuzzy controller perfected with an evolutionary algorithm.

Moreover, the amount of variables can be the problem. Too many variables does not always mean better result. Sometimes too many make the coefficients too small and insignificant (Schneider & Wagemann 2010). This was most likely the case in this experiment, because a lot of rules did not fire.

Another possibility is that the way the data is used made the fuzzy agent not perform well. The fact that manual addition had to be done on the membership functions standard deviation is a warning for bad data handling. A more thorough examination on the rule- generating and exploitation should be done

Nonetheless, in a more constructive approach research could be done to combining expert knowledge and data learning. Fuzzy systems generally perform poorly without the addition of expert knowledge (Pirovano & Lanzi, 2014). The rules the experts give could be combined in similar ways as step 4 in Wang and Mendel (1992). For combining knowledge and data into one system, is fuzzy logic's strength.

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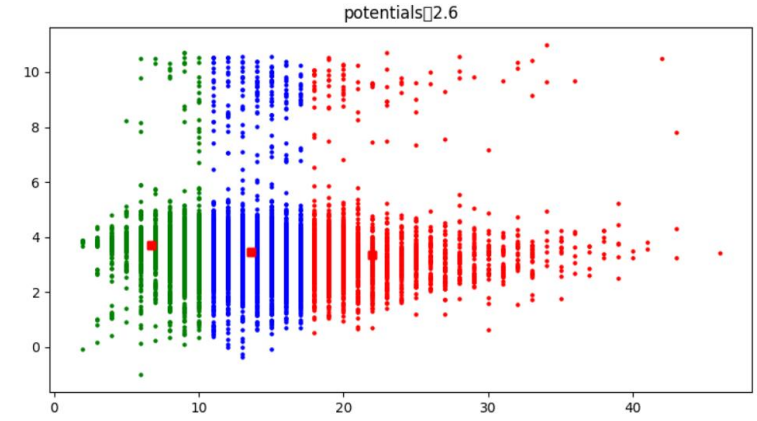
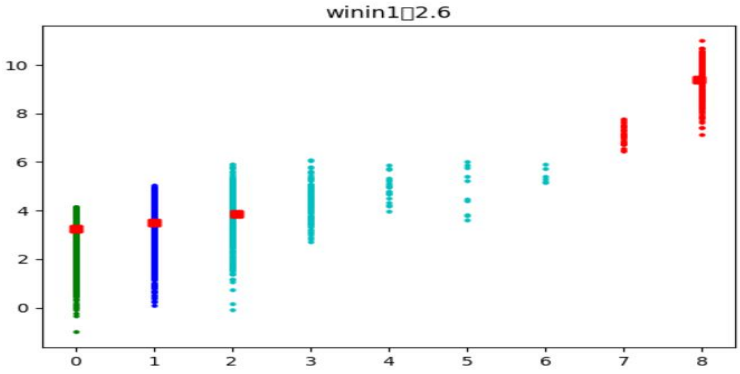
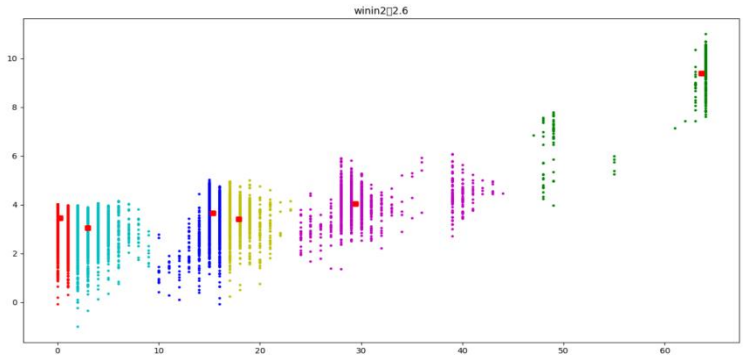
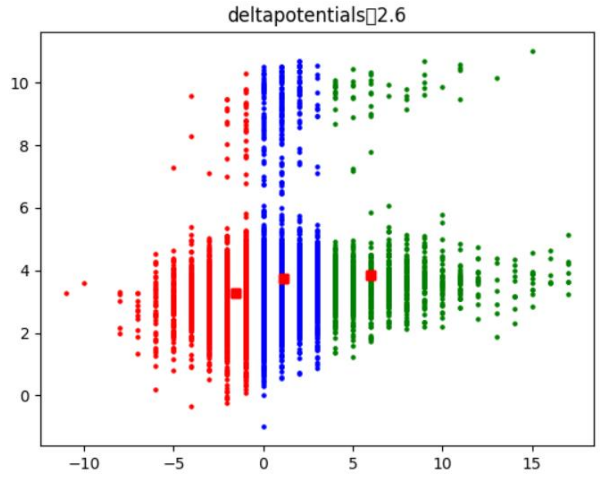
Appendix A: learning memberships





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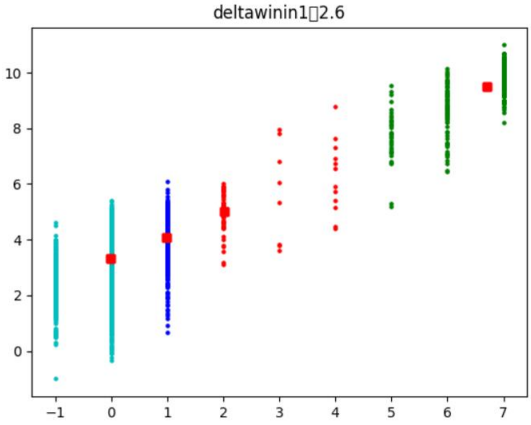
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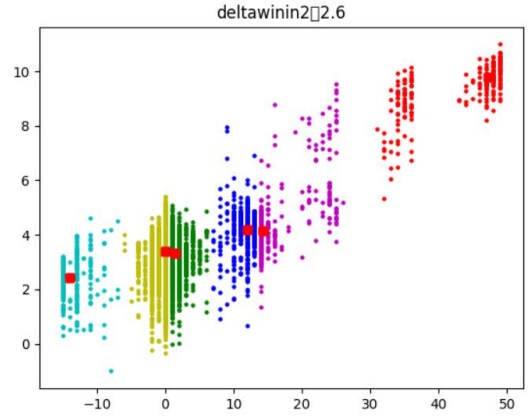
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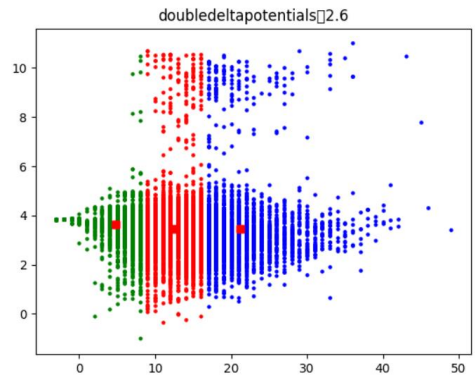
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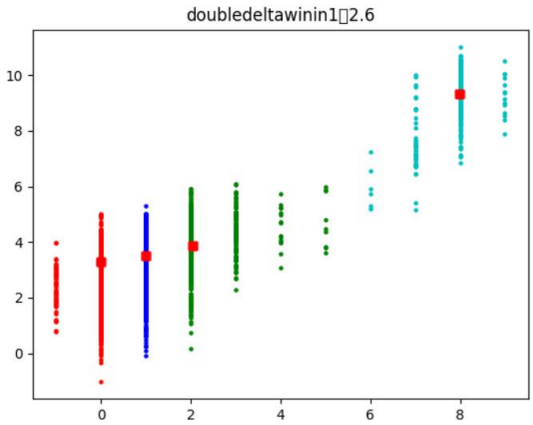
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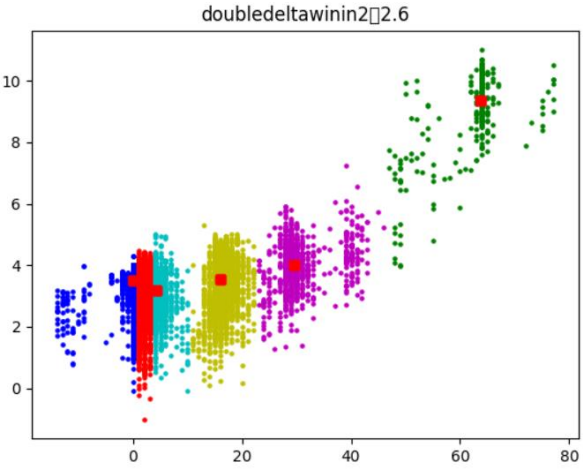
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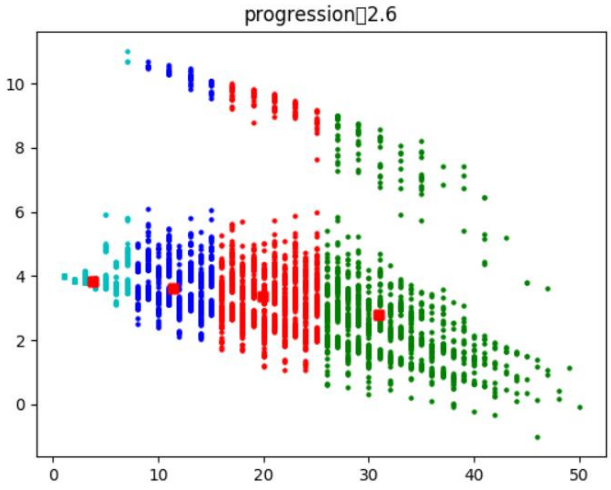
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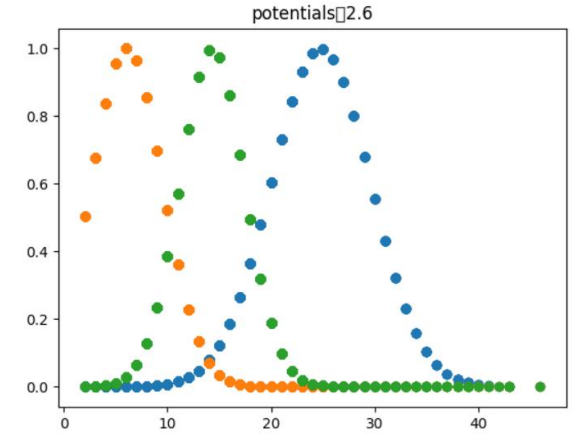
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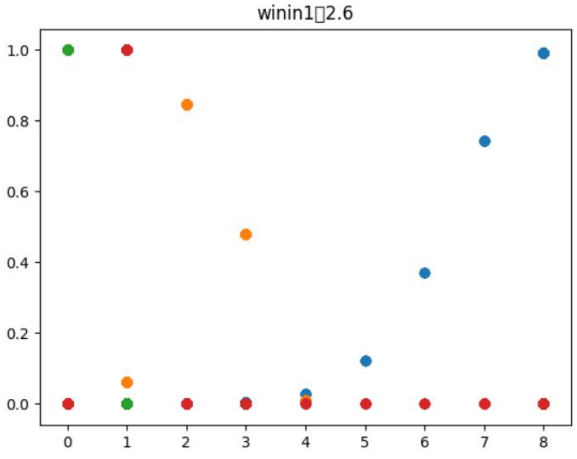
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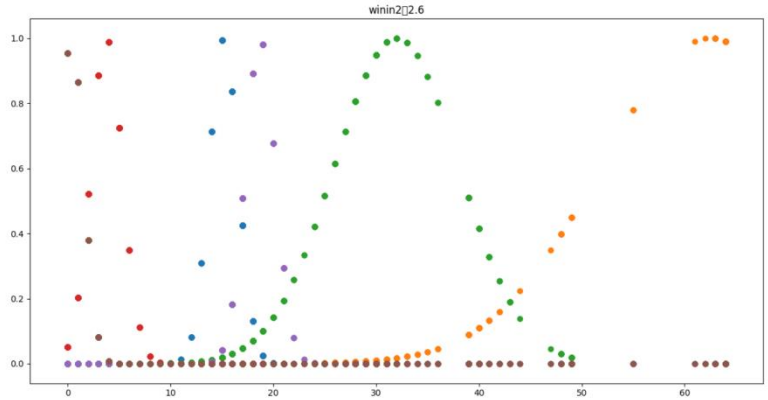
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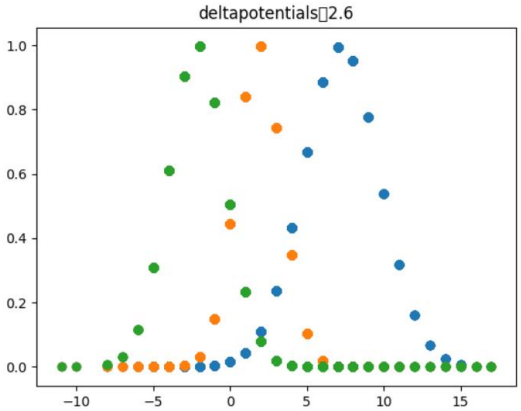
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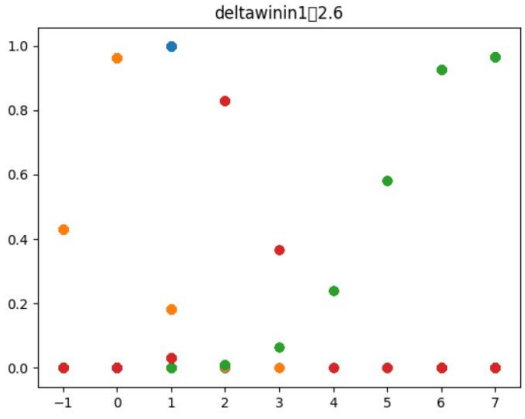
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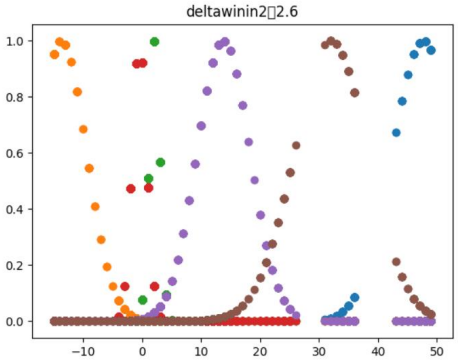
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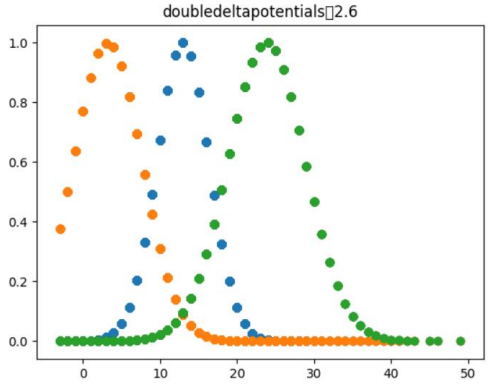
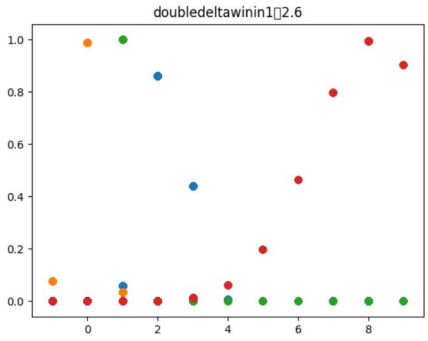
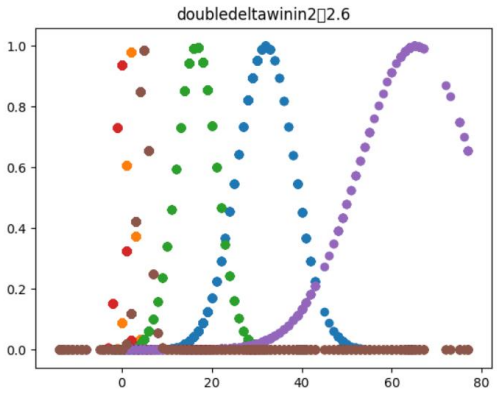
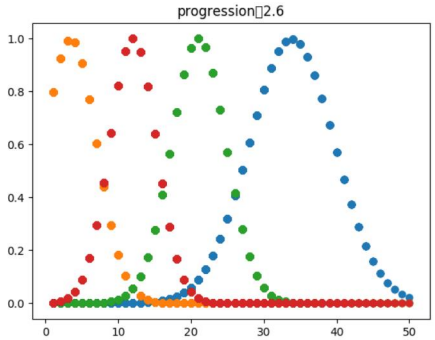

doubledeltapotentials□2.6


doubledeltawinin1□2.6


doubledeltawinin2□2.6


progression□2.6

Appendix B: Fis files

1 fuzzyAgent1 fis file

```
[System]

Name='LeafNodeSystem'

Type='mamdani'

Version=2.0

NumInputs=3

NumOutputs=1

NumRules=30

AndMethod='prod'

OrMethod='probor'

ImpMethod='prod'

AggMethod='sum'

DefuzzMethod='centroid'


[Input1]

Name='GameProgression'

Range=[0 64]

NumMFs=4

MF1='early':'trimf',[-25.6 0 30]

MF2='mid-late':'trimf',[10 42 72]

MF3='late':'trimf',[34 64 89.6]

MF4='mid-early':'trimf',[-10 20 48]


[Input2]

Name='winIn1'

Range=[0 8]

NumMFs=4

MF1='nothing':'trapmf',[0 0 1 1]

MF2='certainWin':'trapmf',[1 2 8 8]

MF3='won':'trapmf',[3 6 8 8]

MF4='good':'trapmf',[0 1 2 3]
```

[Input3]

Name='winIn2'

Range=[0 64]

NumMFs=4

MF1='few':'trimf',[-25.6 0 15]

MF2='some':'trapmf',[0 15 25 40]

MF3='won':'trapmf',[45 60 64 65]

MF4='lots':'trapmf',[15 30 60 64]

[Output1]

Name='ownGain'

Range=[-1 11]

NumMFs=11

MF1='absent':'trapmf',[-1 -1 0 1]

MF2='microscopic':'trapmf',[0 1 2 3]

MF3='tiny':'trapmf',[1 2 3 4]

MF4='slight':'trapmf',[2 3 4 5]

MF5='small':'trapmf',[3 4 5 6]

MF6='some':'trapmf',[4 5 6 7]

MF7='medium':'trapmf',[5 6 7 8]

MF8='reasonable':'trapmf',[6 7 8 9]

MF9='large':'trapmf',[7 8 9 10]

MF10='huge':'trapmf',[8 9 10 11]

MF11='won':'trapmf',[9 10 11 11]

[Rules]

0 2 0, 10 (1) : 1

0 3 0, 11 (1) : 1

1 4 0, 10 (1) : 1

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2 4 0, 9 (1) : 1

3 4 0, 8 (1) : 1

1 1 0, 7 (1) : 1

4 1 0, 6 (1) : 1

2 1 0, 5 (1) : 1

3 1 0, 1 (1) : 1

0 0 3, 11 (1) : 1

1 0 1, 7 (1) : 1

4 0 1, 5 (1) : 1

2 0 1, 3 (1) : 1

3 0 1, 1 (1) : 1

1 0 2, 8 (1) : 1

4 0 2, 8 (1) : 1

2 0 2, 7 (1) : 1

3 0 2, 3 (1) : 1

1 0 4, 9 (1) : 1

4 0 4, 8 (1) : 1

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0 1 4, 6 (1) : 1

0 4 1, 6 (1) : 1

0 4 2, 7 (1) : 1

0 4 4, 8 (1) : 1

0 2 0, 10 (1) : 1

1 3 3, 11 (1) : 1

3 1 1, 1 (1) : 1

2 fuzzyAgent2 and fuzzyAgent3 fis file

[System]

Name='LeafNodeSystem'

Type='mamdani'

Version=2.0

NumInputs=3

NumOutputs=1

NumRules=127

AndMethod='min'

OrMethod='probor'

ImpMethod='prod'

AggMethod='sum'

DefuzzMethod='centroid'

[Output1]

Name='ownGain'

Range=[-1 11]

NumMFs=11

MF1='absent':'trapmf',[-1 -1 0 1]

MF2='microscopic':'trapmf',[0 1 2 3]

MF3='tiny':'trapmf',[1 2 3 4]

MF4='slight':'trapmf',[2 3 4 5]

MF5='small':'trapmf',[3 4 5 6]

MF6='some':'trapmf',[4 5 6 7]

MF7='medium':'trapmf',[5 6 7 8]

MF8='reasonable':'trapmf',[6 7 8 9]

MF9='large':'trapmf',[7 8 9 10]

MF10='huge':'trapmf',[8 9 10 11]

MF11='won':'trapmf',[9 10 11 11]

[Input1]

Name='winin1'

Range=[0 8]

NumMFs=4

MF1='1|4':'gaussmf',[0.000305971185071 0.220034679968]

MF2='2|4':'gaussmf',[8.20400129296 1.56806970103]

MF3='3|4':'gaussmf',[1.01698628033 0.291200998922]

MF4='4|4':'gaussmf',[2.32113862034 0.55889661412]

[Input2]

Name='progression'

Range=[1 64]

NumMFs=4

MF1='1|4':'gaussmf',[0.40900298369 15.57906409119]

MF2='2|4':'gaussmf',[33.8130835241 5.82874647569]

MF3='3|4':'gaussmf',[21.0191560734 3.75449046552]

MF4='4|4':'gaussmf',[64.0 15.18721932131]

[Input3]

Name='doubledeltapotentials'

Range=[-3 49]

NumMFs=3

MF1='1|3':'gaussmf',[23.8306066411 5.00192230181]

MF2='2|3':'gaussmf',[3.20338635516 4.43473803282]

MF3='3|3':'gaussmf',[12.9794650339 3.35315969484]

[Input4]

Name='deltawinin1'

Range=[-1 7]

NumMFs=4

MF1='1|4':'gaussmf',[-0.17501532836 0.636080713338]

MF2='2|4':'gaussmf',[2.29514103644 0.490557467617]

MF3='3|4':'gaussmf',[1.01302920617 0.259181817953]

MF4='4|4':'gaussmf',[6.59816188961 1.54280344653]

[Input5]

Name='deltawinin2'

Range=[-15 49]

NumMFs=6

MF1='1|6':'gaussmf',[-13.6909034652 4.25962546222]

MF2='2|6':'gaussmf',[47.6463222646 5.24500135435]

MF3='3|6':'gaussmf',[32.0188415458 6.24057525174]

MF4='4|6':'gaussmf',[13.7874720384 4.46360668959]

MF5='5|6':'gaussmf',[-0.497138748543 1.22861375964]

MF6='6|6':'gaussmf',[2.04386280699 1.899921955219]

[Input6]

Name='potentials'

Range=[2 46]

NumMFs=3

MF1='1|3':'gaussmf',[14.2983782176 3.11755491284]

MF2='2|3':'gaussmf',[24.7993850847 4.79026461685]

MF3='3|3':'gaussmf',[6.05866162206 3.46511627362]

[Input7]

Name='deltapotentials'

Range=[-11 17]

NumMFs=3

MF1='1|3':'gaussmf',[1.89689635008 1.46973687873]

MF2='2|3':'gaussmf',[-2.15168161852 1.86198545694]

MF3='3|3':'gaussmf',[7.26000667241 2.49069171018]

[Input8]

Name='doubledeltawinin2'

Range=[-14 77]

NumMFs=6

MF1='1|6':'gaussmf',[-0.314241027842 0.881282907168]

MF2='2|6':'gaussmf',[4.77126679401 1.34275678115]

MF3='3|6':'gaussmf',[31.9942211436 6.36671900487]

MF4='4|6':'gaussmf',[1.8415518431 0.835468144209]

MF5='5|6':'gaussmf',[16.5212831949 4.44240419081]

MF6='6|6':'gaussmf',[65.354537477 12.6592926813]

[Input9]

Name='doubledeltawinin1'

Range=[-1 9]

NumMFs=4

MF1='1|4':'gaussmf',[8.19831160219 1.77523888453]

MF2='2|4':'gaussmf',[0.999694652069 0.0707425801551]

MF3='3|4':'gaussmf',[-0.0654699348918 0.410989681851]

MF4='4|4':'gaussmf',[2.30029309908 0.546563594716]

[Input10]

Name='winin2'

Range=[0 64]

NumMFs=6

MF1='1|6':'gaussmf',[16.4797586176 4.40359666466]

MF2='2|6':'gaussmf',[0.139635217424 1.738669344503]

MF3='3|6':'gaussmf',[62.3166865669 10.8543627245]

MF4='4|6':'gaussmf',[2.14415804747 1.86094707619]

MF5='5|6':'gaussmf',[31.952659344 6.37311179832]

MF6='6|6':'gaussmf',[4.81392262926 1.19960969653]

[Rules]

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2 3 1 2 2 1 3 3 1 3, 5 (1) : 1

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