Homework – DSC 540 Week Six

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Part One:

Rule 1: If x is A3 OR y is B1 then z is C1

Rule 2: If x is A2 AND y is B2 then z is C2

Rule 3: If x is A1 THEN z is C3

Let's convert x and y to real life examples for the sake of working through the problem.

Say y is the number of soda, and x is the amount of people.

The output, z, is the chance that the amount of soda will run out.

Then rule one becomes, if amount of soda is high and staff is low, then the risk to run out is low.

Rule two becomes, if the amount of soda is moderate and staff is large then risk is normal.

Rule three becomes, if there is little soda then chance of running out is high.

We begin with the crisp input then for both x1 and y1. The range for x1 is [.2, .5] and the range for y1 is [.1, .7]. These are the crisp ranges that are drawn directly from the given graph.

Then the fuzzified inputs for x1 become max(x =A1) = .5, and min(x = A2) = .2. As well as for y1, the min(y = B1) = .7, and the max(y = B2) = .7.

To calculate these values for the antecedents then we apply them to the fuzzy rules. In the case of multiple antecedents, the AND as well as OR rules are used to combine the values to find a singular consequent.

Then that leaves us with Rule 1:

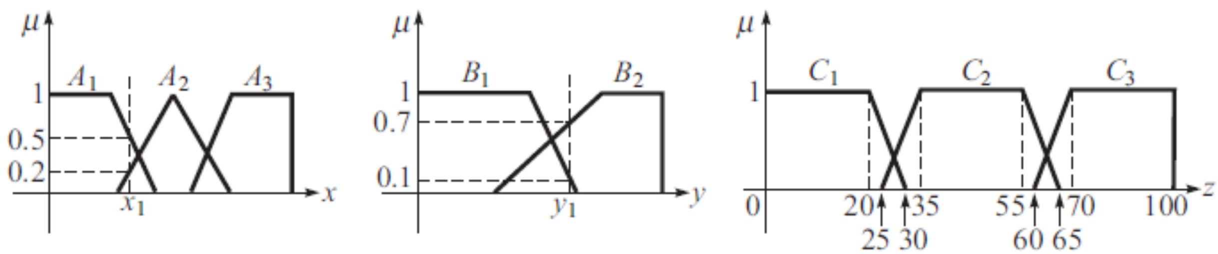
If x is A3 (.0) OR y is B1 (.1) then z is C1 (.1)

Rule 2:

If x is A2 (.2) AND y is B2 (.7) then z is C2 (.2)

Rule 3:

If x is A1 (.5) then z is C3 (.5)



Part 2:

In the article they reference that in a previous paper they utilized a fuzzy model to solve the ocean color inverse problem. This problem is notoriously difficult to solve, not only because the different colors in the ocean, but also because of active constituents such as algae blooms. This is further amplified by the reflective property of the ocean and its floor when viewed from satellite imaging. The ocean color problem can be simplified as deriving the active amount of constituents in the ocean from a reflectance measure of the sea surface. The rules that they created were extracted automatically from simulated data. The method they used fuzzy a clustering algorithm then projected that result onto each input variable. This gave the number of rules, which was equal to the number of clusters, as well as created all the antecedents. The consequent parameters were then created using least squares estimation. This was all optimized in the end using a genetic algorithm, which is a type of evolutionary optimization process. In the article good results were achieved using this type of fuzzy modeling process. However because they determined the number of rules a-priori based on the distribution of data rather than accuracy, there is room for model improvement.

ANFIS is an Adaptive-Network-Based Fuzzy Inference System. This is a type of neural networking model which involves embedding Takagi-Sugeno fuzzy models in a neural network. The adaptive part of this algorithm is the ability for the model to learn from its previous iterations and make improvements on the fuzzy models over time. There is a downfall that comes with the ANFIS system however, in that it does not interact well when there is a high number of inputs. Due to the nature of how the network grows there is an exponential explosion of rules that are created in the center of the network when cases such as if a fuzzy set belongs to different input partitions. To solve this problem, they utilize an evolutionary technique to limit the number of solutions that they consider. This technique is based on a concept called Pareto dominance, which uses multiple performance criteria and finds candidates which maximize the area underneath a Pareto front. When this is all combined the evolutionary technique identified course structures for the fuzzy sets. This happened while the ANFIS computed consequent parameters and tuned the parameters associated with membership functions used in the antecedent rules.

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