In Proceedings of the Sixth International Conference on Cognitive Modeling, 352-353.
Mahwah, NJ: Lawrence Earlbaum.

Applying Fuzzy Logic to Neural Modeling

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What is fuzzy logic?

Fuzzy logic is an extension of Boolean logic which allows intermediate values between True and False. As in Boolean logic, a true statement is expressed by the value "1" and a false statement by the value "0". However, unlike in probability theory, the value must not be interpreted as a confidence level but rather as a Membership Function (MF). Therefore, every statement is "True" to a certain degree and "False" to another.

An interesting property of these MFs is that, because they vary between zero and one, they can be manipulated like probabilities, even though they are interpreted differently.

Fuzzy logic, categorization and neural modeling

Early results in psychology suggest that humans are using fuzzy decision rules. For example, Rosch (1973) has argued in favor of fuzzy boundaries between natural categories. A strong evidence in favor of fuzzy decision rules is seen in an experiment by Labov (1973) which showed that the boundary between the category "bowl" and the category "cup" is a function of size and context and that these categories overlap greatly in medium-size objects (big cups vs. small bowls).

However, connectionist networks, which are increasingly popular in quantitative modeling, are not able to account for these results. For example, multilayer feedforward networks (Rumelhart & McClelland, 1986) learn to fix crisp boundaries and, thereafter, a given item will always be a "bowl" or a "cup". Moreover, it is difficult to understand what processes are actually involved in the classification task. Some methods have been proposed to analyze activation patterns in the hidden layer but the results are unclear.

ANFIS: A neural implementation of fuzzy decision rules

An interesting alternative to standard feedforward connectionist networks would be one which would: 1) implement fuzzy decision rules and, 2) explicitly reveal its decision criterion.

In the field of electrical engineering, Roger Jang (1993) has recently proposed one such model. It is called Adaptive-Network-based Fuzzy Inference System (ANFIS). ANFIS is a multilayer feedforward network which searches for fuzzy decision rules that perform well on any given task. The fuzzy decision rules are implemented as MFs and the model learns the best fitting parameters of the MFs. The architecture of ANFIS is shown in Figure 1.

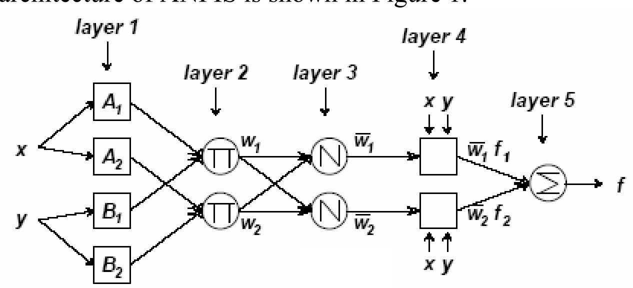


Figure 1: The general architecture of ANFIS (from Roger Jang, 1993).

Even thought ANFIS is a five layer neural network, only two of these layers have adjustable weights (here represented by squares). The first layer is composed of *n* MFs, each implementing a fuzzy decision rule. Any type of distributions can be modeled by MFs and the set of parameters to minimize is determined accordingly[1]. The second layer computes every possible conjunction of the *n* decisions rules[2]. The third layer normalizes the conjunctives MFs in order to rescale the inputs[3]. The fourth layer is a standard Perceptron (Rosenblatt, 1958) and associates every normalized MF with an output (weights are called

[1] More precisely, a MF is a distribution which was not scaled to have an area of one but rather a maximum at one.

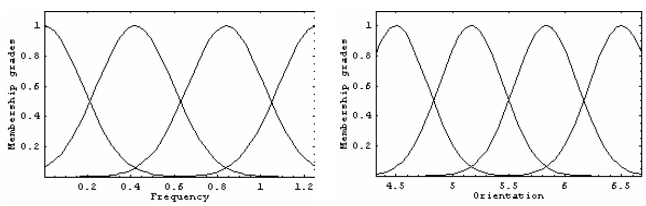
[2] By assuming that the rules are totally independent, the MF of each conjunction is simply the product of the MFs of the conjuncts.

[3] The normalization procedure is: $x_i' = \frac{x_i}{\sum x_j}$.

consequent parameters). Finally, the fifth layer sums the evidences. The output is a real number. The consequent parameters and the MF's parameters are learned by standard backpropagation.

Categorizing Gabor patches using the XOR rule

The learning capabilities of ANFIS (Roger Jang, 1993) were tested in a categorization task. The stimuli used were Gabor patches and the categorization rule was a standard XOR. The sixteen Gabor patches were varying according to their frequency and orientation (Hélie & Cousineau, 2003)[4]. The network was fed directly with the dimension values used to create the stimuli. Because the Cartesian product of our dimension values is of size sixteen, we used sixteen MFs, modeled by Gaussian distributions, evenly dispersed in the stimulus space. The starting MFs are shown in Figure 2.



(*a*) (*b*)

Figure 2: Starting MF in the XOR categorization task. (*a)* MF of the frequency. (*b)* MF of the orientation.

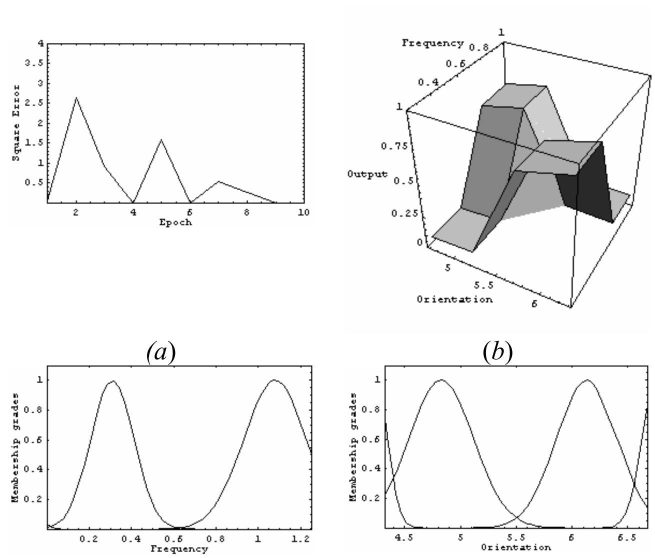
The learning curve and rules learned by ANFIS after 10 epochs of training are shown in Figure 3. As seen, ANFIS has no problem learning the XOR categorization task (a). Moreover, ANFIS learns to discard useless MFs and to use only necessary decision rules (c, d). This result is consistent with results in perceptual learning (Livingston, Andrews & Harnad, 1998) as well as the information reduction theory (Haider & Frensch, 1996). Finally, panel (b) of Figure 3 shows that the two categories are well distinguished by ANFIS.

Conclusion

Fuzzy decision-rules are used by humans in everyday life. Therefore, psychological models should be able to manipulate fuzzy rules. We proposed one such model developed by Roger Jang (1993). ANFIS has the form of a neural network and uses fuzzy decision rules that are transparent (contrary to standard backpropagation models). ANFIS is thus an interesting alternative for neural modeling in having the same capabilities as standard backpropagation networks but in being explicit about it decision rules.

Acknowledgments

This research is supported by scholarships from *Le fonds québecois de la recherche sur la nature et les technologies* and the *Natural Sciences and Engineering Research Council of Canada*.



(c) (d)

Figure 3: Performance of ANFIS on a XOR categorization task. (a) Learning curve of ANFIS. (b) Fuzzy rules learned by ANFIS. (c) Resulting MFs of frequency. (d) Resulting MFs of orientation.

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[4]The frequencies were: {0.25, 0.5, 0.75, 1} and the orientations were:{$3\pi/2$, $133\pi/80$, $73\pi/40$, 2π}.