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# Fuzzy ARTMAP with Group Learning

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## 1. Introduction

Fuzzy ARTMAP achives a synthesis of fuzzy logic and adaptive resonance theory (ART). In this study, we adapt an additional step called "Group Learning" to Fuzzy ARTMAP. This new algorithm is called Fuzzy ARTMAP with Group Learning (FAM-GL). The important feature of the group learning is that creating connections between similar categories. In other words, the FAM-GL learns not only categories but also its connections, namely, groups of the categories. We investigate the behavior of FAM-GL, and discuss the results.

## 2. Proposed Fuzzy ARTMAP

Fuzzy ARTMAP system incorporates two fuzzy ART modules, $\mathrm{ART}_a$ and $\mathrm{ART}_b$, that are linked together through map field $\mathrm{F}^{ab}$. $\mathrm{ART}_a$ is composed of $\mathrm{F}_1^a$ (input layer) and $\mathrm{F}_2^a$ (category layer). $\mathrm{ART}_b$ also has $\mathrm{F}_1^b$ and $\mathrm{F}_2^b$. Input to $\mathrm{ART}_a$ and $\mathrm{ART}_b$ are in the complement code form, for $\mathrm{ART}_a$, $\boldsymbol{I} = \boldsymbol{A} = (\boldsymbol{a}, \boldsymbol{a}^c)$, and for $\mathrm{ART}_b$, $\boldsymbol{I} = \boldsymbol{B} = (\boldsymbol{b}, \boldsymbol{b}^c)$. For the map field (MF), let $\boldsymbol{x^{ab}}$ denote the $\mathrm{F}_{ab}$ output vector, and let $\boldsymbol{w_j^{ab}}$ denote the weight vector from the $j$th node to $\mathrm{F}^{ab}$.

**(FAM-GL1)** $\boldsymbol{A}$ and $\boldsymbol{B}$ are inputted to $\mathrm{F}_1^a$ and $\mathrm{F}_1^b$, respectively.

**(FAM-GL2)** For $\mathrm{F}_2^a$, a winning category J is chosen by choice function $T_j$. J has maximal $T_J$. For $\mathrm{ART}_b$, winning category K is chosen in the same way. Furthermore, for the group learning, the second-winning category, denoted by $\mathrm{J}_2$, is found. namely, $T_{J_2}$ is the second largest.

**(FAM-GL3)** $\boldsymbol{w}_j^{ab}$ and the out put vector $\boldsymbol{y}^b$ of $\mathrm{F}_2^b$ are gived to MF. $\boldsymbol{x^{ab}}$ is calculated by

$$|\,\boldsymbol{x}^{ab}\,| \equiv |\,\boldsymbol{y}^b \wedge \boldsymbol{w}_J^{ab}\,|\,. \tag{1}$$

By Eq. (1), $\boldsymbol{x}^{ab} = 0$ if the prediction $\boldsymbol{w}_J^{ab}$ is disconfirmed by $\boldsymbol{y}_b$. Such a mismatch event triggers an $\mathrm{ART}_a$ search for a better category, as follows.

**(FAM-GL4)** *Match Tracking*: At the start of each input presentation to $\mathrm{ART}_a$, vigilance parameter $\rho_a$ equals a baseline vigilance, $\overline{\rho_a}$. The map field vigilance parameter is $\rho_{ab}$. If

$$|\,\boldsymbol{x}^{ab}\,| \;<\; \rho_{ab}\,|\,\boldsymbol{y}^b\,|, \tag{2}$$

then $\rho_a$ is increased until it is slightly larger than $|\,\boldsymbol{A} \wedge \boldsymbol{w}_j^a\,|\,|\,\boldsymbol{A}\,|^{-1}$. When this occurs, $\mathrm{ART}_a$ search leads either to activation of another $\mathrm{F}_2^a$ node J, if no such node exists, to shutdown of $\mathrm{F}_2^a$ for the remainder of the input presentation. On the other hand, if

$$|\,\boldsymbol{x}^{ab}\,| \;\geq\; \rho_{ab}\,|\,\boldsymbol{y}^b\,|, \tag{3}$$

then follow step the (FAM-GL8).

**(FAM-GL5)** In this step, it is decided whether if a connection is formed. Eq. (3) is satisfied, a connection between the winning category $J$ and the second-winning category $J_2$ is created; $C_{J,J_2} = 0$. The *age* of the connection between the winning category $J$ and the second-winning category $J_2$ is set to zero "refresh" the age; $age_{J,J_2} = 0$. On the contrary, if Eq. (3) is not satisfied, the connection is not formed.

**(FAM-GL6)** The *age* of all categories which directly connect with the winning category $J$ are increased one;

$$age_{J,j}^{new} = age_{J,j}^{old} + 1, \quad j \in N_J, \tag{4}$$

where $N_J$ is set of categories which directly connect with $J$.

**(FAM-GL7)** The connections are removed, if their *age* exceeds a threshold value $AT(t)$;

$$C_{J,j} = 0, \qquad age_{(J,j)} \geq AT(t), \tag{5}$$

$$AT(t) = AT_i (AT_f / AT_i)^{t/t_{max}}, \tag{6}$$

where $t_{max}$ is the learning length, $AT_i$ and $AT_f$ is the initial value and the final value of $AT$, respectively. The steps from (FAM-GL1) to (FAM-GL7) are repeated for all the input data. Therefore, Fuzzy ART-GL makes connections or releases connections at each step.

**(FAM-GL8)** *Learning*: If Eq. (3) is satisfied, weight vectors $\boldsymbol{w}_J^a$, $\boldsymbol{w}_K^b$, $\boldsymbol{w}_J^{ab}$ are updated, as follows.

$$\begin{aligned} \boldsymbol{w}_J^{a(new)} &= \beta_a(\boldsymbol{A} \wedge \boldsymbol{w}_J^{a(old)}) + (1-\beta_a)\boldsymbol{w}_J^{a(old)} \\ \boldsymbol{w}_K^{b(new)} &= \beta_b(\boldsymbol{B} \wedge \boldsymbol{w}_K^{b(old)}) + (1-\beta_b)\boldsymbol{w}_K^{b(old)} \\ \boldsymbol{w}_J^{ab(new)} &= |\,\boldsymbol{y}^b \wedge \boldsymbol{w}_J^{ab}\,| \end{aligned} \tag{7}$$

## 3. Simulation Results

We consider 2-dimensional input data of 300 points, which are random data. The learning results of Fuzzy ARTMAP and FAM-GL are shown in Fig. 1. Rectangles represent categories. From these results, we can see that the categories predicted being outside the circle are represented by dashed lines, and the categories predicted being inside are represented by straight lines in Fig. 1(a). Therefore input data are divied into two kinds of categories. However, we can not see an association between categories. On the other hand, in Fig. 1(b), we can see categories are divided into four groups by four marks. In other words, we can obtain two results of category learning and group learning by FAM-GL.

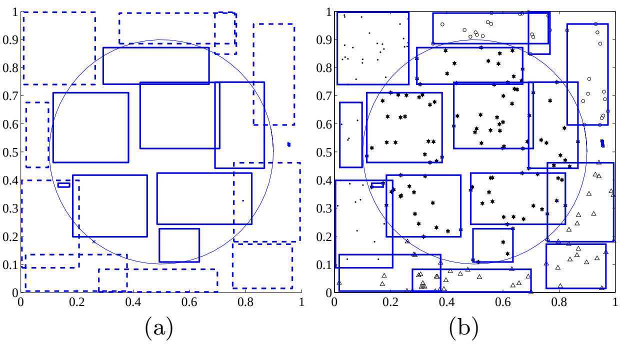


Figure 1: Simulation result. (a) Simulation result of the Fuzzy ARTMAP. (b) Simulation result of the FAM-GL.

## 4. Conclusions

In this study, we have adapted "Group Learning" to Fuzzy ARTMAP. We have investigated its behaviors with application to categorization of 2-dimensional input data, and confirmed the efficiency of FAM-GL.