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# ADAPTIVE RESONANCE THEORY (ART) IN CLASSIFICATION OF SOIL

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**Abstract - Adaptive Resonance Theory (ART) that learn in an unsupervised fashion that can perform in an unaided fashion in a complex environment. The term resonance refers to resonant state of the network in which a category prototype vector matches the current input vector so close enough that the orienting system will not generate a reset signal in the other attentional layer. The networks learn only in their resonant states. Many supervised learning algorithms try to identify several prototypes of exemplars that can serve as cluster centers. K-means, ISODATA and vector quantization technique are examples of decision theoretical approaches for cluster formation. ART structure is a neural network for cluster formation in an unsupervised learning domain. In ART, the number of output nodes cannot be accurately determined in advance.**

***Keywords: Resonance, Vector Quantization technique , Unsupervised learning***

## I. INTRODUCTION

Classical ART Networks are of two types: ART1 which is designed for clustering binary vectors and ART2 accepts analog or continuous valued vectors. These nets cluster inputs by unsupervised learning and the input patterns can be presented in any order. Each time when a pattern is presented, an appropriate cluster unit is chosen and the clusters weights are adjusted to let the cluster unit to learn pattern. The weights on the cluster unit may be considered to be an exemplar for the patterns placed on the cluster.

When the net is trained, one can present training pattern several times. A Pattern may be placed on one cluster unit for the first time and then on a different cluster when it is presented later due to changes in the weights for the first cluster if it has learned other patterns in the mean time. We find in ART architecture, a pattern oscillating among different cluster units at different stages of training, indicating an unstable net.

Stability of the network means that a pattern should not oscillate among different cluster units at different stages of training. Some nets achieve stability by gradually reducing the learning rate as the same set of training set presented many times.

Plasticity is the ability of the net to respond to learn new pattern equally well at any stage of learning. while training patterns are presented many times, this does not allow the net to learn readily a new pattern that is presented for the first time after a number of training epochs have already taken place.

Usually ART nets are designed to be both stable and plastic.

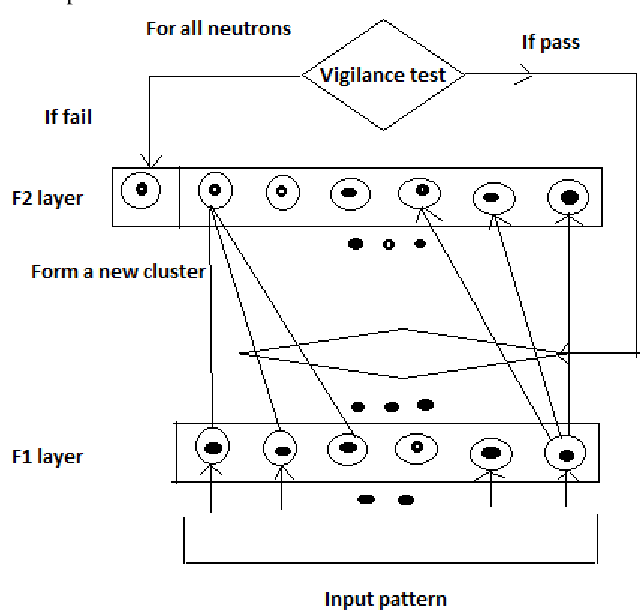


Fig 1.1Simplified ART Architecture

In order to solve stability-plasticity dilemma, it is necessary to add a feedback mechanism between the

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competitive layer and the input layer of the network. This feedback mechanism facilitated the learning of new information without destroying old information and hence, automatic switching between stable and plastic modes. This approach results in two neural networks suitable particularly for pattern classification problems in realistic environment. Also, attention has been paid to structuring ART nets so that neural process can control the rather intricate operation of these sets. This requires a number of neurons, in addition to the input units, cluster units and units for the comparison of the input signal with the cluster units weights.

ART1- This is a binary version of ART. It can cluster binary input vectors.

ART2-This is an analogous version of ART. It can cluster real value input vectors.

ART2A-This network is an ART extension that incorporates a chemical transmitter to control search process in a hierarchal ART structure.

## II. ART1 ARCHITECTURE

The neural network for ART1 model consists of

- A layer of neuron called F1layer(input layer or comparison layer)
- A node for each layer as a gain control unit
- A layer of neuron called F2 layer (output layer or recognition layer)
- Bottom-up connection from F1 to F2 layer
- Top-down connection from F2 to F1 layer
- Inhibitory connection(negative weights) from F2 layer to gain control
- Excitatory connection(positive weights) from gain control to a layer
- Inhibitory connection from F1 layer to reset node and
- Excitatory connection from reset node to F2 layer

The ART1 architecture consists of two layers of neurons called comparison layer and recognition layer. Usually, the classification decision is indicated by a single neuron in the recognition layer that fires. The neurons in the comparison layer respond to input features in the pattern. The synaptic connections between these two layers are modifiable in both the directions. According to learning rules, the recognition layer neurons have inhibitory connections that allow for competition. These two layers constitute attentioned system.

The network architecture also consist of three additional modules labeled Gain1, Gain2 and Reset. In the attentions subsystem, if the match of input pattern with any of the prototype stored occurs, resonance is

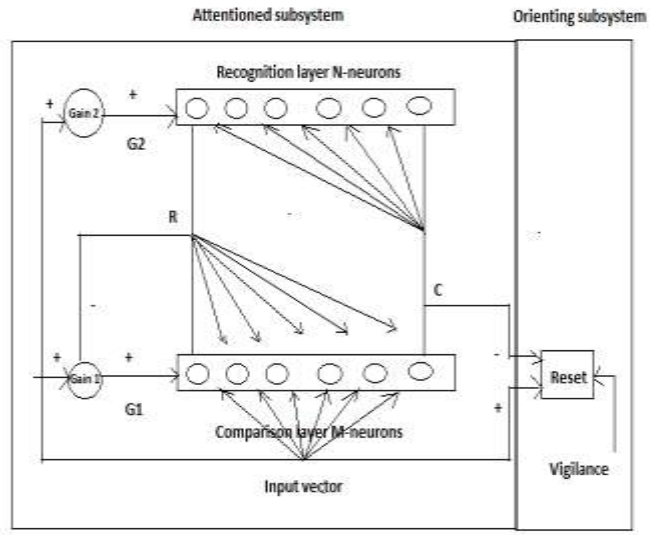


Fig. 2. ART1 Network

established. The orienting subsystem is responsible for sending mismatch between bottom-up and top-down patterns on the recognition layer. The recognition layer response to an input vector is compared to the original input vector through a mechanism called vigilance. When vigilance false below a threshold, a new category must be created and the input vector must be stored into that category.

The recognition layer follows the winner take all paradigm.

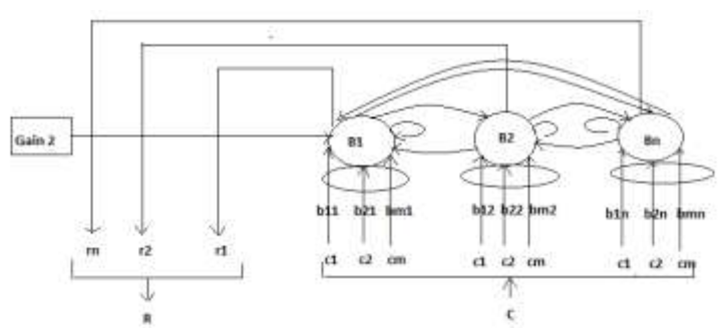


Fig. 3. Recoginition layer

## III. ART1 ALGORITHM

Step1: Apply an input vector I to F1 and F1 activities are calculated as

$$\mathrm{Xi} = \frac{\mathrm{Ii}}{1 + \mathrm{A}(\mathrm{Ii} + \mathrm{B}) + \mathrm{C}}$$

Step2: Calculate the output vector for F1

$$\mathrm{Si}=\mathrm{h}(\mathrm{Xi})=\begin{Bmatrix} 1 & if\ xi > 0 \\ 0 & if\ Xi \leq 0 \end{Bmatrix}$$

Step3:Propagate S forward to F2 and calculate the activities according to

{T}=[bu] {s}

Step4:Only the winning F2 node has a non zero output

$U_J = \begin{cases} 1 & Tj = \max\{Tk\} \forall k \\ 0 & otherwise \end{cases}$

We shall assume that winning node is J

Step5:Propagate the output from F2 back to F1. Calculate the net inputs from F2 to F1 as

{V} =[td]{u}

Step6: Calculate new activities according to

$X_i = \frac{Ii + DVi - B}{1 + A(Ii + DVi) + C}$

Step7: Determine new output values {S} as in step 2

Step8: Determine the degree of match between input pattern and the top-down template as

$\frac{|S|}{|I|} = \frac{\sum_{i=1}^{M} Si}{\sum_{i=1}^{M} Ii}$

Step9: If the above value is < ρ mark J as inactive, Zero the outputs of F2 and return to step1 usingthe original pattern and if the above value is greater than or equal to then continue ρ

Step 10: Update bottom-up weights on J only as $[bu]_{I,J}$

$= \begin{cases} \frac{L}{L-1+|S|} & If\ i\ is\ active \\ 0 & If\ i\ is\ inactive \end{cases}$

Step 11: Update the top-down weights coming from J only to all F1 units.

$[bu]_{I,J} = \begin{cases} 1 & If\ i\ is\ active \\ 0 & if\ i\ is\ inactive \end{cases}$

Step12: Remove the input pattern. Restore all inactive F2 units. Return to step1 with new input pattern.

END ART1

## IV. ILLUSTRATION

Let us perform step by step calculation for following example. Let us define a set of three input vectors as

$[I] = \text{Input} = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

We shall choose the dimension of F1 and F2 as M=5,N=6 respectively.

Choose the values for the following parameters as

A=1;B=1.5;C=5;D=0.9; ρ=0.9

Let us take the first input vector as

$[I] = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$

Let us initialize top-down weights by adding positive value of 0.2 to (B-1)/D giving

$\frac{0.2+(B-1)}{D} = \frac{0.2+0.5}{0.9} = 0.456$

$[td] = \begin{bmatrix} 0.756 & 0.756 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0.756 & 0.756 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0.756 & 0.756 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0.756 & 0.756 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0.756 & 0.756 & 0.756 & 0.756 & 0.756 & 0.756 \end{bmatrix}$

Since M=5 and L=5, weights on F2 units are all initialized to slightly less than the given value (say 0.1)( which is obtained as

$\left(\frac{L}{(L-1+M)}\right)$-0.1 $=\left(\frac{5}{9}\right)$-0.1= 0.456

$[bu] = \begin{bmatrix} 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \end{bmatrix}$

We can now begin actual processing. We shall start with simple input vector as

$\langle I_1 \rangle^T = \langle 0\ 0\ 0\ 1\ 0 \rangle^T$

Step1 : After the input vector is applied, the F1 activities become

$\langle X_1 \rangle^T = \langle 0\ 0\ 0\ 0.118\ 0 \rangle^T$

Step 2: The output vector S is written as

$\langle S \rangle^T = \langle 0\ 0\ 0\ 1\ 0 \rangle^T$

Step 3: Propagating this output vector to F2 the net inputs to all F2 units will be identical.

$\{T\} = [bu] * \{S\} = ] = \begin{bmatrix} 0.455 \\ 0.455 \\ 0.455 \\ 0.455 \\ 0.455 \\ 0.455 \end{bmatrix}$

Step 4: Calculate b{u} as

$\langle U \rangle^T = \langle 1\ 0\ 0\ 0\ 0 \rangle^T$

Since all unit activities are equal, simy take the first unit as winner

Step 5: Calculate {V} as

$\{V\} = [td] * \{u\} = ] = \begin{bmatrix} 0.756 \\ 0.756 \\ 0.756 \\ 0.756 \\ 0.756 \end{bmatrix}$

Step 6 : Calculate new activity values on F1 as

$\langle X \rangle^T = \langle -0.123\ -0.123\ -0.123\ 0.023\ -0.123 \rangle^T$

Step 7 : Only unit 4 has a posiive activity and hence new outputs are

$\langle S \rangle^T = \langle 0\ 0\ 0\ 1\ 0 \rangle^T$

Step 8: Caluculate $\frac{|S|}{|I|}$=1> ρ=0.9

Step 9: There is no reset and resonance reached

Step 10: Update bottom-up weight matrix as

$[bu] = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \end{bmatrix}$

Step 11: Update top-down weights as

$$[td]=\begin{bmatrix} 0 & 0.756 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0 & 0.756 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0 & 0.756 & 0.756 & 0.756 & 0.756 & 0.756 \\ 1 & 0.756 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0 & 0.756 & 0.756 & 0.756 & 0.756 & 0.756 \end{bmatrix}$$

That completes the cycle of the first input pattern. Now, let us apply second pattern that is orthogonal to I1 as

$<I2>^T = <0\ 0\ 1\ 0\ 1>^T$

$<T>^T = <0\ 0.911\ 0.911\ 0.911\ 0.911\ 0.911>^T$

Unit 1 definitely loses. We select unit 2 as winner.

$<U>^T = <1\ 0\ 0\ 0\ 0>^T$

$<V>^T = \{td\}\ \{u\} = <0.756\ 0.756\ 0.756\ 0.756\ 0.756>^T$

$<X>^T = <-0.123\ -0.123\ 0.0234\ -0.123\ -0.0234>^T$

The resultingmatches the input vector $<0\ 0\ 1\ 0\ 1>^T$ and hence there is no reset. Now, the bottom-up matrix is given by

$$[bu]=\begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0.833 & 0 & 0.833 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \end{bmatrix}$$

Now, the top-down matrix is given by

$$[td]=\begin{bmatrix} 0 & 0 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0 & 0 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0 & 0 & 0.756 & 0.756 & 0.756 & 0.756 \\ 1 & 1 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0 & 1 & 0.756 & 0.756 & 0.756 & 0.756 \end{bmatrix}$$

Now, let us apply the third input vector as

$<I3>^T = <0\ 0\ 0\ 0\ 1>^T$

$<U>^T = <0\ 1\ 0\ 0\ 0\ 0>^T$

$<V>^T = <0\ 0\ 1\ 0\ 1>^T$

In this case, the equilibrium activities are

$<X>^T = <-0.25\ -0.25\ -0.087\ -0.25\ 0.0506>^T$

With only one positive activity. The new output pattern is <0 0 0 0 1> which exactly matches with input pattern. So, no reset occurs.

Eventhough unit 2 on F2 had previously encoded an input pattern, it gets recorded now to match the new input pattern that is a subset of the original pattern. The new weight matrices are

$$[bu]=\begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \\ 0.456 & 0.456 & 0.456 & 0.456 & 0.456 \end{bmatrix}$$

$$[td]=\begin{bmatrix} 0 & 0 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0 & 0 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0 & 0 & 0.756 & 0.756 & 0.756 & 0.756 \\ 1 & 1 & 0.756 & 0.756 & 0.756 & 0.756 \\ 0 & 1 & 0.756 & 0.756 & 0.756 & 0.756 \end{bmatrix}$$

If we return to the superset vector $<0\ 0\ 1\ 0\ 1>^T$, the initial forward propagation to F2 yields activities as X = <-0.25 -0.25 -0.25 0.0506 -0.25>

The outputs are <0 0 0 1 0>. This time resonance has reached pattern 1 on unit 1

A Program ART1 developed in FORTRAN produces following output

resonance has been on unit1 pattern1
resonance has been on unit2 pattern2
resonance has been on unit3 pattern3
network not stable
resonance has been on unit1 pattern1
reset with pattern2 on unit2
resonance has been on unit3 pattern2
resonance has been on unit3 pattern3
network not stable
resonance has been on unit1 pattern1
reset with pattern2 on unit3
reset with pattern2 on unit2
resonance has been on unit4 pattern2
resonance has been on unit2 pattern3
network not stable
resonance has been on unit1 pattern1
resonance has been on unit4 pattern2
resonance has been on unit2 pattern3
network stable

## V. APPLICATION

**Classification of soil**

The potential of ART1 based pattern recognizer to recognize real data has been studied. only four data is chosen from the table and identified for classification.

**Table 1.Soil data**

| Color of soil | Gravel % 18 | Sand % 82 | Fine grain % 84 | Liquid limit 58 | Plastic limit 34 | IS type |
|---|---|---|---|---|---|---|
| 0.2 | 0.111 | 0.682 | 0.5 | 0.508 | 0.529 | 1 |
| 0.1 | 0 | 0.329 | 0.869 | 0.711 | 0.735 | 2 |
| 0.2 | 0 | 0.529 | 0.670 | 0.576 | 0.676 | 3 |
| 0.7 | 0 | 0.353 | 0.845 | 0.677 | 1 | 4 |

**Color of soil**

0.1-brown
0.2- Brownish grey
0.7-Yellowish red

**IS type**

1-Clayey sand
2-Clay with medium compressibility
3-Clay with low compressibility

4-Slit with medium compressibility
First the real data is converted to integer and given as inputs to ART1. ART1 is able to identify the soil as 1,2,3,4. the output of the program is as follows:
resonance has been on unit1 pattern1
reset with pattern2 on unit1
resonance has been on unit2 pattern2
resonance has been on unit3 pattern3
reset with pattern4 on unit3
reset with pattern4 on unit1
resonance has been on unit4 pattern4
network not stable
reset with pattern1 on unit4
reset with pattern1 on unit3
resonance has been on unit1 pattern1
reset with pattern2 on unit1
resonance has been on unit2 pattern2
reset with pattern3 on unit4
reset with pattern3 on unit1
resonance has been on unit3 pattern3
reset with pattern4 on unit1
resonance has been on unit4 pattern4
network stable

## VI. CONCLUSION

If any pattern is repeated, we will be able to recognize the pattern. ART1 is an elegant theory that addresses stability-plasticity dilemma. The network relies on resonance. It is a self-organizing network and does the categorization by associating individual neuron of the F2 layer with the individual patterns. By employing so called 2/3 rule, it ensures stability in learning process.

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