2D1432 Artificial Neural Networks and Other Learning Systems

- Adaptive Resonance Theory (ART)

Plasticity vs. Stability Dilemma

- Plasticity: Network needs to learn new patterns
- Stability: Network needs to memorize old patterns
- Human brain: face recognition

Plasticity vs. Stability Dilemma

- Backpropagation
  - New patterns require retraining of the network
  - No Stabilization
- Kohonen maps (SOM)
  - Stabilization achieved by decreasing learning rate
  - Decreasing learning rate reduces plasticity

ART Characteristics

- Goal: Design a neural network that preserves its previously learned knowledge while continuing to learn new things.
- Biologically plausible: ART has a self-regulating control structure that allows autonomous recognition and learning no supervisory control or algorithmic implementation.

ART Terminology

- STM : Short term memory
  - Refers to the dynamics of neural units (recognition, matching)
- LTM : Long term memory
  - Refers to the adaptation of weights (learning)
- Gain control :
  - control structure to activate/deactivate search and matching

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ART Basic Architecture

- **STM F2**
  - Each node represents a prototype (template)
  - Competitive dynamics (winner takes all)
  - Performs template selection
- **STM F1**
  - Performs template matching
  - Matches template from layer F2 with the input
- **Inputs**
  - Just stores the input to F1, no dynamics

ART Basic Algorithm

- Presentation of input vector to layer F1
- Until resonance between F1 and F2
  - Determine winning node in F2 that has the highest activation in response to input. (adaptive filter)
  - Matching between template and input
  - If Mismatch is severe enough
    - Inhibit template node
- Layers F1 and F2 are in resonance: Adapt top-down and bottom-up LTM weights

ART Algorithmic Level

- X = \{x_1, ..., x_M\}, x_i \in \{0,1\} (F1 nodes)
- |X| = \sum_i x_i
- Z = \{z_1, ..., z_M\}, z_i \in \{0,1\} (templates)
- \{w_{j1}, ..., w_{jM}\}, w_{ji} \in [0,1] (adaptive filters)
- A = B \cap C bitwise and
  - a_i = 1 if b_i = 1 and c_i = 1

- Initialize top-down weights z_{ji} = 1
- Initialize bottom-up weights w_{ji} randomly ensuring w_{ji} < 1/M
- Apply input I
- J = \{v_1, ..., v_N\} : list of candidate prototypes
- Repeat until resonance
  - Find winning node v_j \in J in F2 with largest value of I w_{ji}
  - Compute X = I \cap Z (matching)
  - If |X|/|I| > \rho (resonance occurs, \rho = vigilance parameter)
  - Else delete v_j from J
- If resonance update template Z and adaptive filter W
  - top-down expectations z_{ji} = z_{ji} \cap x_i
  - bottom-up filter w_{ji} = 1/|X| if x_i = 1, else w_{ji} = 0
**ART 2/3-Rule**

- Nodes in layer F1 are *supraliminally* activated if they receive a signal from at least two out of three possible sources.
  - Bottom up input I
  - Top down input Z
  - Gain control
  - A node in F1 that receives input from only one of the sources is *subliminally* activated.

**ART System Implementation**

- Pattern X inhibits A and generates the bottom up signal S, which is transformed by the weights W into signal T.
- F2 is a competitive network so the node v_j which receives the largest total input is activated.

- Pattern V at F2 generates the top-down signal pattern U which is transformed by the top-down templates into the expectation pattern Z.
- Pattern also V inhibits F1 gain control.
ART System Implementation
- As a result only those nodes X* in F1 that represent bits in intersection of input I and expectation Z remain supraliminally activated.
- If Z mismatches I this results in a decrease in the total inhibition from F1 to A.
- If the mismatch is severe enough A can no longer be prevented from releasing a reset signal to F2. This resets the active node at F2.
- The vigilance parameter ρ determines how much mismatch will be tolerated.

Leaky Integrator Neuron
- ε dn(t)/dt = -n(t) + p(t)
- Fix point n=p

Shunting Model
- ε dn(t)/dt = -n(t) + (b^+ - n(t))p^+(t) - (n(t) + b^-)p^-(t)
- Fix point: n=(b^+p^+-b^-p^-)/(1+p^+-p^-)

Once a match is found that allows F1 to inhibit the orienting subsystem the attentional subsystem is in resonance and the activations remain stable.
- Learning (adapting LTM) only takes place when layers F1 and F2 are in resonance.

After the F2 node is inhibited its top down expectation is eliminated and X can be reinstated at F1.
- The previous chosen node at F2 remains inhibited until F2’s gain control is disengaged by removal of the input pattern.
Input Normalization

\[ \varepsilon \frac{dn(t)}{dt} = -n(t) + (b^+ - n(t)) W^+ p(t) - (n(t) + b^-) W^- p(t) \]

Fix point: \( n = \frac{(b^+ W^+ - b^- W^-) p}{1 + (W^+ - W^-) p} \)

Excitatory input: \( W^+ = I \), \( w^+_{ij} = \delta_{ij} \)

Inhibitory input: \( W^- \), \( w^-_{ij} = 1 - \delta_{ij} \)

On-center/Off-surround pattern

LTM Learning Law

Hebbian learning rule with decay

\[ dw_{ij}(t)/dt = \alpha (-w_{ij}(t) + n_i(t) n_j(t)) \]

For ART learning and forgetting should be turned off if the post-synaptic neuron \( n_i \) is not active.

\[ dw_{ij}(t)/dt = \alpha n_i(t) (-w_{ij}(t) + n_j(t)) \]

Choose LTM time constant \( \alpha \) much smaller than STM time constant \( \varepsilon \)

LTM Learning Law

ART Layer 1

Thresholded output

\( a^2 = 1 \) if \( n_i > 0 \)
\( a^2 = 0 \) if \( n_i \leq 0 \)

\( p + W^2 a^2(t) \) sum of input vector \( p \) and L2-L1 expectation

Assume the \( j \)-th neuron in layer 2 won the competition

\( W a^2(t) \) : gain control term, inhibitory input to layer 1

\( w^-_{ij} = 1 \)

Since there is only one winning neuron in layer 2, gain control will be 1 if layer 2 is active and 0 otherwise
**ART Layer 1**

- Case layer 2 is inactive $a_j^2=0$
- $\varepsilon \frac{dn_1^2(t)}{dt} = -n_1^2(t) + (b^+ - n_1^2(t)) p_i$
- Fixpoint: $n_1^i = b^+/p_i$ / $(1+p_i)$
-硬lim转移函数：$a_i=p_i$
- Summary: If layer 2 is inactive the output $a$ of layer 1 is the same as the input $p$.

**ART Layer 2**

- $\varepsilon \frac{dn_1^2(t)}{dt} = -n_1^2(t) + (b^+ - n_1^2(t)) (W^+ \sigma(n_1^2(t)) + W^{1:2} a^i(t)) - (n_1^2(t) + b^-)$
- 兴奋输入：$W^+ \sigma(n_1^2(t)) + W^{1:2} a^i(t)$
- 抑制输入：$W \sigma(n_1^2(t))$
- $W^+, W^-$，on-center, off-surround反馈连接
- $W^{1:2}$ prototype patterns
- $b^+ = 1, b^- = 1 \quad n_1^2(t) \in [-1,1]$
- Fixpoint behavior:
  - $a_j^2 = 1$ if $w_j^{1:2} a^1 = \max \{ w_k^{1:2} a^1 \}$
  - $a_j^2 = 0$ otherwise
- Matlab demo: with $W^{1:2} = [0.5 0.5, 1.0 0.0]$

**Other ART Architecture**

- ART2：处理连续输入模式（Carpenter&Grossberg 1987）
- ARTMAP：异联识记模式，适合于监督训练，由两个ART模块组成，一个接收输入，另一个接收期望输出（同向异联识记Hopfield网络见实验2）（Carpenter&Grossberg&Reynolds 1991）
- Fuzzy ART和模糊ARTMAP：融入模糊逻辑，模板可以赋值为模糊值（程度的成员）而非二值成员