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Sequential Memory with ART: A Self-Organizing Network Capable of Learning Sequences of Patterns

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Abstract - A model which extends the adaptive resonance theory model to sequential memory is presented. This new model learns sequences of events and recalls a sequence when presented with parts of the sequence. The ART model is modified by creating interconnected sublayers within ART's \(F_2\) layer. Nodes within \(F_2\) learn temporal patterns by forming recency gradients within LTM. Versions of the ART model like ART 1, ART 2, and fuzzy ART can be used.

1. Introduction

Sequential memory is the memorization of events, their temporal order, and their timing relationships. Patterns of both space and time make up a large percentage of patterns that are encountered. Many important applications make use of these type of patterns. Some of these applications are variable-rate speech perception, sensory-motor planning, and 3D visual object recognition.

The SMART model is a modification of the adaptive resonance theory (ART) models described by Grossberg (1976b) and the avalanche model described by Grossberg (1969). The ART models are very good at self-organizing and self-stabilizing recognition codes in response to input patterns. However, these models include no method of associating recognition codes with each other. Sequential memory requires the ability to associate recognition codes.

2. Design Principles of SMART

SMART's representation of temporal order is similar to the representation the avalanche network uses. The design philosophy of SMART can be uncovered by analyzing how an avalanche network could be made to learn, recall, and recognize patterns.

The standard avalanche network illustrated in Figure 1a can not perform recognition. For it to perform recognition it should have bottom-up LTM from \(v_1\) to \(v_2\). Since the network already has top-down LTM the ART mechanism is an obvious method of achieving stability in the network. This combination of Avalanche and ART is the primary inspiration for SMART.

Suppose we want the avalanche to learn two or more similar sequences. The avalanche network can only learn one sequence. What if each outstar is replaced by a group of outstars as is illustrated in Figure 1b. The groups of outstars can be sequentially activated. Within each group the outstar which most closely matches the input will encode the current pattern.

For different sequences to be differentiated the outstars can be connected together with LTM. Each outstar can then activate the next outstar in the sequence (Figure 1c). This arrangement is similar to the adaptive context-modulated avalanche described in Grossberg 1986.

The network in Figure 1c is fine as long as two sequences do not share the same item, but if two sequences do share the same item then the sequences can not be distinguished during replay (Figure 2a). The outstar representing the shared item points to both sequences. A solution is to allow the outstar to point to more than just one of the next items (Figure 2b). The outstars will maintain activity for a duration longer than just the duration of one item presentation and sample activity of outstars which are subsequently activated. Two sequences with shared items can be distinguished because when the outstar representing the shared item is reached other outstars pointing to the correct sequence are still active (Figure 2c). Temporal order is now represented by sets of spatial patterns (Figure 2d).

3. The SMART Architecture

The overall SMART architecture is illustrated in Figure 3. SMART contains the traditional \(F_1\) layer of ART. Layer \(F_2\) is composed of several different layers. The \(F_2\) sub-layers are the groups of outstars mentioned above (Figure 1b). These sub-layers are activated sequentially in a manner similar to the outstars in the avalanche network. Each of these sub-layers are competitive so that only one outstar in the sub-layer is selected at a time. This selection is determined by both bottom-up input and left to right input.

The \(F_2\) sub-layer which is active is selected by the second type of layer within \(F_2\), the region select layer. The region select layer is a competitive layer which has one cell for each sub-layer in \(F_2\). When the cell for a sub-layer is active, that sub-layer and possibly surrounding sub-layers become active. The cells in the region select layer

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Figure 1. Variations of the avalanche network. The normal configuration of the avalanche network is illustrated in A. The GO signal starts the sequential activation of the outstars which can either learn or recall a pattern. B represents a network which can learn two sequences. The context modulated avalanche is illustrated in C.

Figure 2. Temporal order as spatial patterns. A illustrates a situation in which two sequences, abcd and uvce, share a pattern, c. After c is recalled the sequence may not be correctly replayed because c points to both d and w. In B nodes have connections to three subsequently activated nodes. The second sequences can be correctly recalled in C because sustained activity at u and v will activate w instead of d. Temporal order is represented as sets of spatial patterns in D.

receive input from the sub-layers they activate and the region select cell immediately to the left. If bottom-up input does not match categorizations in the sub-layers then the sub-layers will be activated sequentially, otherwise the sub-layers will be selected based on which sub-layer has the best match.

Figure 4 illustrates an example of an input sequence to SMART. The sequence of patterns A,B,C are presented to the SMART network. When A is presented the first cell in the region select layer starts to become active (due to random factors) and the first sub-layer is selected. Once the first sub-layer is active, the first cell in the sub-layer wins the competition. The next input, B, is presented and activity in the first sub-layer shuts off. The second cell in the region select layer is then activated by the first cell. By random chance, the third cell in the second sub-layer is selected. A LTM connection between the node representing A to the node representing B is formed. When C is presented the third cell in the region select layer is selected and the second node of the third sub-layer is activated. A connection is formed between the node for B to the node for C and a weaker connection is formed from the node for A to the node for C.
3. The SMART network. SMART has an $F_1$ and an $F_2$ layer like ART but the $F_2$ layer is split into many sub-layers. The sub-layers are composed of a layer of cell-groups which form a recurrent competitive field that implements choice. The active sub-layer is chosen by the region select layer. As different inputs are presented the sub-layers are sequentially activated. Cell-groups which were previously active sample currently active cell-groups via the intralayer $F_2$ LTM.

Figure 3.

Sequence of Activation

Region Select Layer

Cell Group $F_2$

Sub-layer

Intralayer $F_2$ LTM

Input

Figure 4. Sequence of three inputs presented to the SMART network. The first input, A, activates cell $v_{1,1}$. When B is presented cell $v_{2,3}$ becomes active and cell $v_{1,1}$ samples $v_{2,3}$. When C is presented and $v_{3,2}$ becomes active, activity at $v_{1,1}$ has decreased. Both $v_{1,1}$ and $v_{2,3}$ sample $v_{3,2}$ but the $v_{2,3}$ to $v_{3,2}$ LTM is larger.

3.1. SMART Sub-Layers

Sub-layers in $F_2$ provide several capabilities in addition to that of sequential activation of nodes. If every outstar can have a connection to every other outstar and if the number of items is large then the number of connections can be very large. The number of connections can be reduced by limiting connections to sub-layers which are close. Since the sub-layers are sequentially activated, these are the only connections which are needed under most circumstances.

Also, when sequential activation is not strong and input from the sub-layers primarily controls selection of sub-layers, clumping can occur within SMART. Similar patterns will be placed into the same sub-layer since the sub-layer is more strongly activated by the input and sends this activity to the region select layer. Even if the pattern
3.2. Cell Groups

Unfortunately the capabilities required of the nodes in the sub-layers can not be achieved with just one cell. The basic design of the SMART cell group has three cells. The principle component of the cell group is the activity cell. This cell samples activity of the F1 layer and competes with the other cells in the sub-layer to become the active cell. If this cell is in a competitive network, how can it sustain activity to sample activity of other nodes (Figure 5a)? The answer is that it can not and that a new cell, the forward cell, should be introduced. The forward cell retains activity for a period of perhaps three to four pattern presentations. Figure 5b illustrates the cell group at this point. The forward cell is activated by the combination of a forward signal and the activity of the activity cell. The forward signal is similar to the reset signal and is generated when a new pattern is presented to the network.

The forward cell samples activity of cell groups which are subsequently activated so that it forms a spatial pattern which represents the temporal order of the next several patterns. During recall the forward cell sends output to cell-groups which represent patterns which occur next in the sequence.

The backward cells is the other type of cell in the cell group (Figure 5c). The backward cell receives input from other cells and sends this input to the activity cell. The forward cell is separated from the activity cell for several reasons. The most obvious reason is that this cell should stay on for a fixed period of time as opposed to the variable amount of time the activity cell is on (which is due to the variable amount of time an input pattern could be present). The time has to be fixed so that other cell groups have a fixed sampling time so that the weight size will not be a function of item duration. If weights were a function of item duration then a sequence could become disconnected if an input pattern remained on for a shorter period than the rest of the patterns.

3.3. Region Select Layer

The region select layer is responsible for selecting the active sub-layer(s) within $F_2$. It is a competitive layer with a cell which corresponds to each sub-layer in $F_2$. Activity from the cell groups within a sub-layer is summed at the region select layer cell corresponding to that sub-layer. The cell at the most active sub-layer wins the competition. The winner of this competition then sends feedback to the sub-layers which causes the most active sub-layer to be the only active sub-layer so that sequential activation of cells can occur.

3.4. Reset of $F_2$ nodes and $F_2$ regions

A primary component of all ART models is the ability to deactivate an active node when a mismatch occurs. For the ART 3 system (Carpenter & Grossberg 1990), depletable transmitters were used to reduce activities at nodes. The SMART model also uses depletable transmitters to deactivate nodes.

The activity cells receive excitatory input from three sources: the backward cell, $F_1$, and region select layer nodes. In order to prevent an activity cell from becoming active the activity cell must not receive inputs from any of the three sources. The inputs from the forward cell, $F_1$, and the region select layer can be gated by a depletable...
chemical transmitter. When a node becomes active the transmitter is depleted and the node will have a very small chance of winning the competition.

When a new event is to be learned the entire region which was previously activated may need to be inhibited in order to allow sequential activation of the regions. An $F_2$ region can be inhibited if the corresponding region select layer node is not allowed to win the competition. This inhibition can be achieved if input to the recurrent competitive field, RCF, is also gated through a depletable transmitter. An entire region of $F_2$ nodes can therefore be inhibited for a short time after it is activated.

In order to simplify the design of the region select layer an additional cell was added. This cell sums the input to each node in the RCF. Input from this cell is then gated through a depletable transmitter to the RCF cells.

4. Discussion

The SMART architecture presented in this paper is a general purpose architecture which can be used as a subsystem in more complex systems. A motor planning system in which SMART remembers sequences of movements is one such system. A SMART network in which the inputs consisted of object locations and limb postures could recall sequences of limb postures. An invariant 3D object recognition network can be built by using SMART to learn and recognize an aspect-graph. (Koenderink and van Doorn 1979).

The SMART model does not specify either the $F_1$ layer, its interaction with the $F_2$ layer, or the reset signal generation and can therefore be used with many different variations of ART such as ART 1 (Carpenter and Grossberg 1987a), ART 2 (Carpenter and Grossberg 1987b), and Fuzzy ART (Carpenter, Grossberg, and Rosen 1991).

5. References


