

# MODIFIABLE AUTOMATA SELF-MODIFYING AUTOMATA

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## I - INTRODUCTION.

One of the most important features of living beings which seems universal is perhaps their ability to be modified in a functional way.

In order to model this characteristics, we designed asynchronous deterministic systems linked by their input(s) and output(s) to a deterministic process which are capable to be functionally modified.

The rules which govern the evolution of these systems (and the initial conditions) are randomly chosen at the beginning of the process and once and for all.

These systems always stabilise and then have the property to maintain their program.

This kind of stability explains the self-programming properties of living beings in a general way and of the nervous system in particular.

### 1 - 1 - Functional modifications of living beings.

An essential property of living beings is their capability for functional modification whenever stimuli occur.

The neuron has two simultaneous functions: to transmit the nerve impulses and to modify the transmission of the nerve impulses. When a sensory organ sends impulses through the nervous system, the transfer of the subsequent impulses is modified.

Authors have shown that the spatial organisation of the neurons in the kitten's visual cortex is set up by the nerve impulses its brain receives from the retina in the first weeks of its life.((8) Kalil et al)

Usually, scientific models use stable functions. Apart from Kahlmann's filters and all adaptive systems, e.g. neural networks, the circuit remains the same after the signal has gone through it.

### 1 - 2 - Capacity to self-program.

Living beings have the capacity to:

#### A - Understand a new message.

In the telecommunications domain, data transmission between an emitter and a receiver always presupposes a coding convention, whereas living beings find a meaning in the message while having no knowledge of the emitter's cipher.

A meaningful example is to set Dove's prisms in front of both eyes of a man. These devices inverse vision: the left side becomes the right one, and the top part of the visual field becomes the bottom part. After a few weeks, the landscape is normally perceived. ((4) Gonshor and Melvill)

#### B - Have appropriate reactions.

Let us quote the following experience: one cuts an ape's ocular muscles, crosses them and then sutures: The oculo-motricity is then reversed, i.e. when the animal wants to look to the right side, the eyes turn toward the left, and a command to turn toward the top adjusts toward the bottom. After a few weeks, ocular motility and balance of the animal are normal.

Our examples are chosen in the field of neurology which is more familiar to us; we could also have quoted convincing examples in other domains such as the ability of the reticulo-endothelial system to synthesize antigens, of white ants to dig their gallery according to the galleries they have already dug, or even of the ability of plants to react in an appropriate way after complex mechanical stimuli.

It seems that living beings possess the capacity to program themselves without any programmer (self-programming).

This self-programming property should be explained by the particular type of stability of functionally modifiable systems .

### 1 - 3 - Other models

A -Some authors have studied the dynamics of automata networks where connections and truth tables are randomly chosen at the beginning and once and for all, which implies that internal rules remain fixed. (Quenched model) ((7) Kauffman, (3) Fogelman Soulié)

B -Other authors have studied the dynamics of automata networks where rules are randomly modified at each step. (Annealed model) ((2) Derrida, Stauffer).

C -The recent connectionist models (threshold automata networks)((3) Fogelman Soulié) are networks where automata are functionally modified by inputs, but the program which functionally modifies the networks is outside the network (back propagation of the gradient for example). According to our views, we would prefer this network, which is functionally modifiable by its inputs to stabilize by itself.

D -Finally, von Neumann ((10) von Neumann) and other authors ((1) E.F. Codd) ((9) Thatcher) ((5) Greussay) in order to continue von Neuman's last work have built self-reproducing automata.

In this paper, we introduce a new framework which will allow us to model those properties. We present self-modifying automata (SMA) in section 2 and their dynamics in section 3, we then introduce modifiable automata (MA) in section 4 and show their equivalence to SMA in section 5. Section 6 gives results on the dynamical behaviour of MA.

## **II - SELF-MODIFYING AUTOMATON (S.M.A.).**

### **2 - 1 - Components.**

Let  $F$  be the set of mappings applying  $N$  into  $N$ . ( $N$  is the set of integers)

$$F = \{f: N \rightarrow N\}$$

1 - Let  $F_A$  be the subset of  $F$  containing the mappings of  $F$  applying a finite subset  $A$  of  $P(N)$  into  $A$ .

$$F_A = \{f: A \rightarrow A\}$$

2 - We call  $S$  the set of *images* of the mappings of  $F_A$ .

$$S = \bigcup_{f \in F_A} f(A)$$

$S \subseteq A$  according to the very definition of  $F_A$ .

3 - We call  $C$  *encoding mapping* applying  $S$  into  $F_A$ :

$$C: S \rightarrow F_A$$

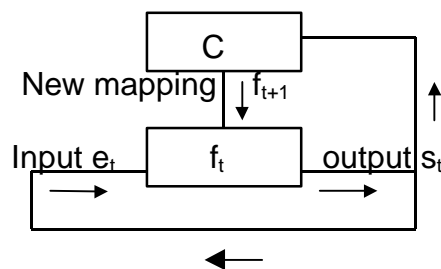
### **2 - 2 - Functioning.**

Thus, from 2 values:

- 1 - An input value  $e_t \in A$
- 2 - A mapping  $f_t \in F_A$

are calculated two others values:

- 1 - An output value  $s_t \in S$
- 2 - A new mapping  $f_{t+1} \in F_A$



We now define a *self-modifying automaton* (SMA) as a mapping  $A_1$  applying the set  $F_A \times A$  into itself.

$A_1$  is a fixed mapping defined by  $C$  and defining the dynamics:

$$A_1(f_t, e_t) = (f_{t+1}, e_{t+1}) = [C \circ f_t(e_t), f_t(e_t)] \quad (1)$$

Note that  $A_1$  only requires  $C$  for its definition.

### III - DYNAMICS.

#### 3 - 1 - Initialisation.

At the beginning of the process and once and for all:

1- We randomly build the mapping  $C$  creating an arbitrary correspondence between the elements of the set  $S$  and the mappings of the set  $F_A$ . This defines a SMA  $A_1$ .

2 - We randomly choose an element  $(f_0, e_0)$  of the set  $F_A \times A$ .

#### 3 - 2 - Trajectory.

The behaviour of the self-modifying automaton  $A_1$  is characterised by a *trajectory* composed of points  $(f_t, e_t)$  of the set  $F_A \times A$ .

### 3 - 3 - Convergence.

Let  $(f_0, e_0) \in F_A \times A$  be the initial point of the trajectory.

Let  $(f_1, e_1), (f_2, e_2), \dots, (f_m, e_m)$  be the successive points of the automaton trajectory.

Definition. A self-modifying automaton *converges* whenever a point of its trajectory  $(f_k, e_k)$  is identical to a previous point  $(f_{k-p}, e_{k-p})$ . It then indefinitely goes through a limit cycle composed of the point  $(f_k, e_k)$  and the  $p$  points between this two identical points  $(f_k, e_k)$  and  $(f_{k-p}, e_{k-p})$ .

A self-modifying automaton is a deterministic device, and the cardinality of set  $F_A \times A$  is finite. Therefore such an automaton necessarily converges.

We will study two values:

- 1 - The length  $p$  of the limit cycle; i.e. its *period*.
- 2 - The *transient length*  $\tau = k-p$ .

### 3 - 4 - Fixed point.

We call *fixed point* a cycle of length  $p = 1$ .

Ending in a fixed point is the most frequent event as we will see further.

Let  $(f, e) \in F_A \times A$

The sufficient condition for  $(f, e)$  to be a fixed point is:

$$f(e) = e \quad (2)$$

$$C \circ f(e) = f \quad (3)$$

Combining expressions (2) and (3), we obtain:

$$C(e) = f \quad (4)$$

Let us consider the transformation  $C^{-1}$ :

$$C^{-1}(f) = \{s \in S : C(s) = f\}$$

$$(4) \Rightarrow e \in C^{-1}(f)$$

Hypothesis: From now on, we suppose that  $C^{-1}(f)$  is identical to  $\{e\}$ :

$$C^{-1}(f) = e \quad (5)$$

Substituting value  $e$  of equality (5) in (3), we infer:

$$\boxed{C \circ f \circ C^{-1}(f) = f}$$

## IV - MODIFIABLE AUTOMATON (M.A.).

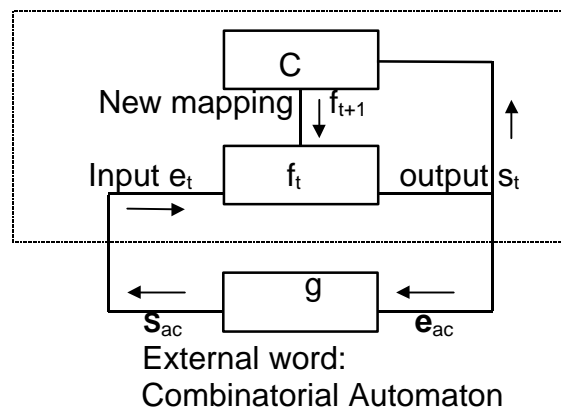
### 4 - 1 - Definition.

In the previous description, the output value of the self-modifying automaton is transferred to the input:  $s_{t-1} = e_t$ .

Let  $g$  be an element of the set  $F_A$  defining a combinatorial automaton (G). Its input value  $e_{ca}$  and its output value  $s_{ca}$  are linked together by the mapping  $g$ :

$$s_{ca} = g(e_{ca})$$

Let us connect a self-modifying automaton with the fixed external automaton (G) :  $e_t = s_{ca}$  et  $e_{ca} = s_t$ . G will play the role of an external source i.e. environment, sending signals to the SMA



We can write:

$$\begin{aligned} C \circ f_t(e_t) &= f_{t+1} \\ g \circ f_t(e_t) &= e_{t+1} \end{aligned} \quad (6)$$

(7)

These equalities define a new dynamics  $A_3$ :

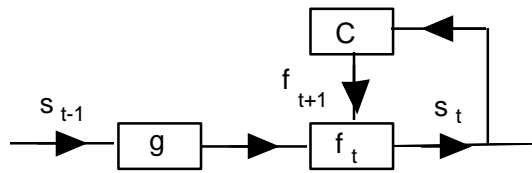
$$A_3(f_t, e_t) = (f_{t+1}, e_{t+1}) = [C \circ f_t(e_t), g \circ f_t(e_t)]$$

### 4 - 2 - Fixed point.

We can write:

$$s_t = f_t \circ g(s_{t-1}) \quad (8)$$

$$C(s_t) = f_{t+1} \quad (9)$$



Let us suppose that  $(f, e) \in F_A \times A$  defines a fixed point, and let  $f(e)$  be equal to  $s$ . Then the equalities (8) and (9) become:

$$\begin{aligned} s &= f \circ g(s) \\ C(s) &= f \end{aligned} \quad (10)$$

(11)

Let us consider as before the transformation  $C^{-1}$ :

$$\begin{aligned} C^{-1}(f) &= \{s \in S : C(s) = f\} \\ (11) \Rightarrow s &\in C^{-1}(f) \end{aligned}$$

Hypothesis: We suppose  $C^{-1}(f)$  to be identical to  $\{s\}$ , then we can write:  $s = C^{-1}(f)$

We eliminate  $s$  in equality (10):

$$C^{-1}(f) = f \circ g \circ C^{-1}(f) \quad (12)$$

and we finally get:

$$\boxed{C \circ f \circ g \circ C^{-1}(f) = f}$$

## V - SELF-MODIFYING AUTOMATON EQUIVALENT TO A MODIFIABLE AUTOMATON.

The same notation as in the previous paragraph will be used here, except for a new encoding mapping  $C_2$  which is defined as follows:

$$\forall s \in S, C_2(s) = C(s) \circ g$$

Equalities (8) and (9) of the previous paragraph now become:

$$s_t = f_t \circ g(s_{t-1}) \quad (13)$$

$$C_2(s_t) = C(s_t) \circ g = f_{t+1} \circ g \quad (14)$$

The equalities (13) and (14) define the dynamics  $A_2$ :

$$\begin{aligned} A_2(f_t \circ g, s_{t-1}) &= (f_{t+1} \circ g, s_t) \\ &= [C_2 \circ f_t \circ g(s_{t-1}), f_t \circ g(s_{t-1})] \end{aligned} \quad (15)$$

Suppose that in equality (1) of paragraph 2:

$$A_1(f_t, e_t) = (f_{t+1}, e_{t+1}) \\ = [C \circ f_t(e_t), f_t(e_t)] \quad (1)$$

we replace  $e_t \rightarrow s_{t-1}$ ,  $f_t \rightarrow f_t \circ g$  and  $C \rightarrow C_2$ , then we obtain (15).

Therefore the dynamics  $A_1$  of the self-modifying automaton is identical to the dynamics  $A_2$  of the modifiable automaton connected with a combinatorial automaton.

#### Fixed point.

Using the same method as in paragraphs III and VI, we obtain the equality characterising a fixed point:

$$C_2 \circ g \circ f \circ C_2^{-1}(g \circ f) = g \circ f$$

### VI - Period and transient length of MA.

#### 6 - 1 - Stabilisation after k changes of input value.

Let  $B_A$  be the class of all MA on the set  $F_A^?A$  of cardinality  $m$ . By choosing, for each MA, its associated function  $C$  at random, we endow  $B_A$  with a probability distribution. We are interested in various probabilities within that class  $B_A$ .

Let us first denote  $Pr_1(m, k)$  the probability for a MA in class  $B_A$  to stabilise after  $k$  steps.

That MA will necessarily have its first  $k$  points different and the  $k+1$  th point identical to one of the previous points.

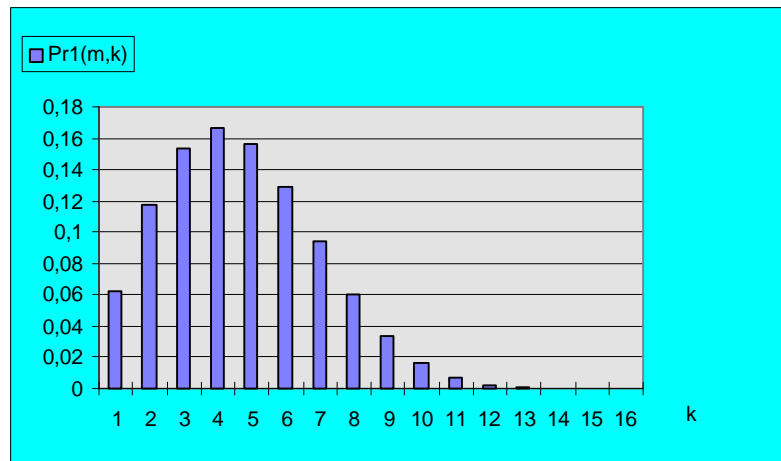
By evaluating the probabilities of the various events, it is easy to show that:

$$Pr_1(m, k) = [(m-1/m)][(m-2/m)] \dots [(m-k+1/m)][k/m] =$$

$$Pr_1(m, k) = P(m, k) * k / m^{k+1}$$

where  $P(m, k)$  represents the number of arrangements of  $m$  objects taken  $k$  by  $k$ .

It is possible to show that the distribution  $Pr_1(m, k)$  has its maximum for  $k = m^{1/2}$ . We display below an example of  $Pr_1(m, k)$  for  $m = 16$ :



This figure shows that: Most probably a MA will stabilize after very few states.

### 6 - 2 - Stabilization in a loop of length p after a transient length $\tau$ .

k being given, the period p can take any of the k values on  $[1, k]$  while  $\tau$  takes any of the k values in  $[0, k-1]$ .

Let us consider a MA stabilized in a limit cycle after k changes of its input value. The probability in the set of all possible MA for this event is equal to  $Pr_1(m, k)$ . Then the k+1 th point is equal to one of the k previous points.

Let us call  $e_{ik}$  the event "stabilization in a limit cycle of length i after k changes of the input value" and  $Pr(e_{ik})$  the probability of event  $e_{ik}$  in the class  $B_A$  of all MA.

Then  $Pr(e_{1k}) = Pr(e_{2k}) = \dots = Pr(e_{kk-1}) = Pr(e_{kk})$  because all states in  $[1, k]$  are equally probable candidates for being re entered at step k+1.

$e_{1k} \cap e_{2k} \cap \dots \cap e_{kk-1} \cap e_{kk} = \emptyset$  and  $Pr(e_{1k}) + Pr(e_{2k}) + \dots + Pr(e_{kk-1}) + Pr(e_{kk}) = Pr_1(m, k)$

Therefore,  $Pr(e_{1k}) = \dots = Pr(e_{k-1k}) = Pr(e_{kk}) = Pr_1(m, k) / k$ .

Let us call  $Pr_2(m, p)$  the probability of period p in the class of MA on a set  $F_A \times A$  of cardinality m.

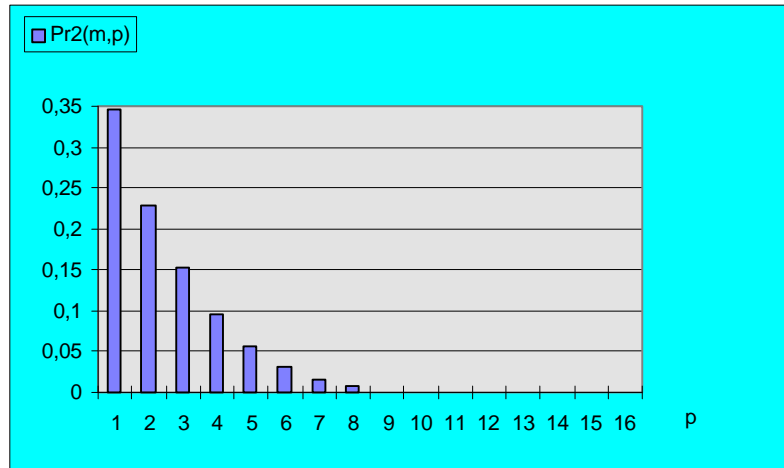
Then the distribution  $Pr_2(m, p)$  is obtained from  $Pr_1(m, k)$ :

$$Pr_2(m, p) = \sum_{k=p}^m Pr_1(m, k)/k = \sum_{k=p}^m P(m, k) m^{k+1}$$

By a similar reasoning, we obtain the probability of transient length  $\tau$  in the class  $B_A$ .

$$\Pr_3(m, \tau) = \sum_{k=\tau}^{m-1} \Pr_1(m, k)/k = \sum_{k=\tau}^{m-1} P(m, k) m^{k+1}$$

We display below an example of  $\Pr_2(m, p)$  for  $m = 16$ :



This figure shows that most MAs will enter a limit cycle after a very short transient time (85% of chance to enter a limit cycle after only 4 iteration steps). Furthermore, the period of the limit cycle will be very small (85% of chance to have one smaller than 5).

These stabilisation properties do arise for small values of  $m$ . For large values, the distributions tend to be uniform. This implies that self-programmable automata must operate on reduced dimensions sets  $A$ . In that case, a MA most probably will stabilise in a fixed point.

$$\text{Maximum (mode) of the distribution } \Pr_1(m, k) = \frac{m!}{(m-k)!} \frac{k}{m^{k+1}}$$

We must find a value of  $k$  which satisfies  $\frac{\Pr_1(m, k+1)}{\Pr_1(m, k)} < 1$  and

$$\frac{\Pr_1(m, k-1)}{\Pr_1(m, k)} < 1.$$

$$\text{We can write } \frac{\Pr_1(m, k+1)}{\Pr_1(m, k)} = \frac{\frac{m!}{(m-k-1)!} \frac{k+1}{m^{k+2}}}{\frac{m!}{(m-k)!} \frac{k}{m^{k+1}}} = \frac{(k+1)(m-k)}{mk}$$

$$\text{and } \frac{\Pr_1(m, k-1)}{\Pr_1(m, k)} = \frac{\frac{m!}{(m-k+1)!} \frac{k-1}{m^k}}{\frac{m!}{(m-k)!} \frac{k}{m^{k+1}}} = \frac{(k-1)m}{k(m-k+1)}$$

$$\text{hence } \frac{(k+1)(m-k)}{mk} < 1 \text{ and } \frac{(k-1)m}{k(m-k+1)} < 1.$$

The computation of these two inequalities gives:

$k^2 - k < m < k^2 + k$  which is the solution : Only one integer  $k$  satisfies these inequalities. If we replace  $k$  by  $k+1$  in the expression  $k^2 - k$ , we obtain  $(k+1)^2 - (k+1) = k^2 + k$ .

$$\text{In addition if } \frac{\Pr_1(m, k+1)}{\Pr_1(m, k)} = 1 \text{ then } m = k^2 + k.$$

Cumulative distribution function of  $\Pr_1(m, k)$ .

$$\text{We have to demonstrate that } \sum_{k=m-1}^m \Pr_1(m, k) = \frac{m!}{1!m^{m-1}}$$

The values of  $k = m$ ,  $k = m-1$  and  $k = m-2$  satisfy this equality :

$$\sum_{k=m}^m \Pr_1(m, k), \sum_{k=m-1}^m \Pr_1(m, k) \text{ et } \sum_{k=m-2}^m \Pr_1(m, k):$$

$$\Pr_1(m, m) = \frac{m!}{m^m},$$

$$\Pr_1(m, m) + \Pr_1(m, m-1) = \frac{m!}{m^m} + \frac{m!(m-1)}{m^m} = \frac{m!}{m^{m-1}},$$

$$\Pr_1(m, m) + \Pr_1(m, m-1) + \Pr_1(m, m-2) = \frac{m!}{m^{m-1}} + \frac{m!(m-2)}{2!m^{m-1}} = \frac{m!}{2!m^{m-2}},$$

let us suppose that  $\sum_{k=m-1}^m \Pr_1(m, k) = \frac{m!}{1!m^{m-1}}$ , then

$$\sum_{k=m-1-1}^m \Pr_1(m, k) = \frac{m!}{1!m^{m-1}} + \frac{m!}{(1+1)!m^{m-1-1}}$$

$$\text{when } k=1, \sum_{k=1}^m \Pr_1(m, k) = \frac{m!}{m!m^{m-m}} = 1.$$

The cumulative distribution function of  $\Pr_1(m, k)$  is  $\sum_{k=1}^{m-1} \Pr_1(m, k)$

and we have  $\sum_{k=m-1}^m \Pr_1(m, k) + \sum_{k=1}^{m-1} \Pr_1(m, k) = 1$  therefore

$$\sum_{k=1}^{m-1} \Pr_1(m, k) = 1 - \sum_{k=m-1}^m \Pr_1(m, k) = 1 - \frac{m!}{1!m^{m-1}}$$

$$\boxed{\sum_{k=1}^{m-1} \Pr_1(m, k) = 1 - \frac{m!}{1!m^{m-1}}}$$

$$\boxed{\text{Expression of } \Pr_2(m, p) = \sum_{k=p}^m \frac{\Pr_1(m, k)}{k}}$$

$$\begin{aligned} \Pr_2(m, p) &= \sum_{k=p}^m \frac{\Pr_1(m, k)}{k} = \frac{m!}{(m-p)!m^{p+1}} + \dots + \frac{m!}{(m-m)!m^{m+1}} \\ &= \frac{m!}{m^{m+1}} \left[ \frac{m^{m-p}}{(m-p)!} + \dots + \frac{m^1}{1!} + 1 \right] \end{aligned}$$

Let us compute  $\sum_{p=1}^m \Pr_2(m, p)$  result of which is equal to 1.

$$\Pr_2(m, m) = \sum_{k=m}^m \frac{\Pr_1(m, k)}{k} = \frac{m!}{(m-m)!m^{m+1}} = \frac{m!}{m^{m+1}} \text{ has one term.}$$

$$\Pr_2(m, m-1) = \sum_{k=m-1}^m \frac{\Pr_1(m, k)}{k} = \frac{m!}{m^{m+1}} + \frac{m!}{m^m} = \frac{m!}{m^{m+1}} \left[ 1 + \frac{m^1}{1!} \right] \text{ has two}$$

terms.

$$\Pr_2(m, p) = \frac{m!}{m^{m+1}} \left[ \frac{m^{m-p}}{(m-p)!} + \dots + \frac{m^1}{1!} + 1 \right] \text{ has } m-p+1 \text{ terms.}$$

$$\Pr_2(m, 1) = \frac{m!}{m^{m+1}} \left[ \frac{m^{m-1}}{(m-1)!} + \dots + \frac{m^1}{1!} + 1 \right] \text{ has } m \text{ terms.}$$

$$\sum_{p=1}^m \Pr_2(m, p) \text{ has } p \text{ times the term } \frac{m!}{m^{m+1}} \frac{m^{m-p}}{(m-p)!} \text{ hence}$$

$$\frac{m!}{(m-p)!} \frac{p}{m^{p+1}} = \frac{m!}{m^{m+1}} \frac{pm^{m-p}}{(m-p)!}$$

Therefore:

$$\begin{aligned}
\sum_{p=1}^m \Pr_2(m, p) &= \frac{m!}{m^{m+1}} \sum_{p=1}^m p \frac{m^{m-p}}{(m-p)!} = \frac{m!}{m^{m+1}} \sum_{p=0}^m [m - (m-p)] \frac{m^{m-p}}{(m-p)!} \\
&= \frac{m!}{m^{m+1}} \left[ \sum_{p=0}^m m \frac{m^{m-p}}{(m-p)!} - \sum_{p=0}^m (m-p) \frac{m^{m-p}}{(m-p)!} \right] \\
&= \frac{m!}{m^{m+1}} \left[ \sum_{p=0}^m m \frac{m^{m-p}}{(m-p)!} - \sum_{p=0}^m m \frac{m^{m-p-1}}{(m-p-1)!} \right] \\
&= \frac{m!}{m^{m+1}} \left[ m \frac{m^{m-p}}{(m-p)!} \right]_{p=0} = \frac{m!}{m^{m+1}} \frac{m^{m+1}}{m!} = 1
\end{aligned}$$

This result is obvious considering that  $\frac{m!}{(m-p)!} \frac{p}{m^{p+1}}$  is the expression of  $\Pr_1(m, k)$  for  $k = p$ .

In this case, we can write :

$$\sum_{p=1}^m \Pr_2(m, p) = \Pr_1(m, 1) + \dots + \Pr_1(m, m) = \sum_{k=1}^m \Pr_1(m, k) = 1.$$

$\Pr_2(m, p)$  tends to uniform distribution when  $p \rightarrow \infty$ .

$$\begin{aligned}
\Pr_2(m, p) &= \sum_{x=p}^m \frac{m!}{(m-x)! m^{x+1}} = \frac{m!}{(m-p)! m^{p+1}} + \frac{m!}{(m-p-1)! m^{p+2}} + \dots + \frac{m!}{(m-p)! m^{p+1}} \\
&= \frac{m!}{m^{m+1}} \left[ \frac{m^{m-p}}{(m-p)!} + \frac{m^{m-p-1}}{(m-p-1)!} + \dots + \frac{m^1}{1!} + 1 \right]
\end{aligned}$$

$$\frac{\Pr_2(m, p)}{\Pr_2(m, p+1)} = \frac{\left[ \frac{m^{m-p}}{(m-p)!} + \frac{m^{m-p-1}}{(m-p-1)!} + \dots + \frac{m^1}{1!} + 1 \right]}{\left[ \frac{m^{m-p-1}}{(m-p-1)!} + \dots + \frac{m^1}{1!} + 1 \right]}$$

$$\begin{aligned}
&= \frac{\Gamma(m-p+1, m)}{(m-p)! e^{-m}} = \frac{\Gamma(m-p+1, m)}{\frac{\Gamma(m-p, m)}{(m-p-1)! e^{-m}}} = \frac{\Gamma(m-p+1, m)}{(m-p)\Gamma(m-p, m)}.
\end{aligned}$$

( $\Gamma$  is the incomplete gamma function).

$\frac{\Pr_2(m, p)}{\Pr_2(m, p+1)} \rightarrow 1$  when  $m \rightarrow \infty$  and the distribution  $\Pr_2(m, p)$

tends to uniform distribution, the probability that  $s_{ma}$  stabilises in 1-cycle decreases when the number of its internal states  $m$  increases

and  $s_{ma}$  is a bad model of model because this property supposes a stabilisation almost exclusively in 1-cycle.

### **VIII - CONCLUSION.**

We have shown:

- The equivalence between self-modifying and modifiable automata.
- The prevalence of  $p=1$  length period and of  $\tau = 0$  transient length for automata on low-cardinality space.

This work demonstrates that the self-programming capability can be obtained easily from the dynamical behaviour of modifiable automata on low-cardinality space.

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