TRIBUTE TO ERIC

J. Demongeot Université Grenoble Alpes

70

HISTORY 1921

- B. Russell *The Analysis of Mind*, Londres, Allen & Unwin,

abolished nor harmonized with perception. If the room had remained unchanged, we might have had only the feeling of familiarity without the definite remembering; it is the change that drives us from the present to memory of the past.

We may generalize this instance so as to cover the causes of many memories. Some present feature of the environment is associated, through past experiences, with something now absent; this absent something comes before us as an image, and is contrasted with present sensation. In cases of this sort, habit (or association) explains why the present feature of the environment brings up the memory-image, but it does not explain the memory-belief. Perhaps a more complete analysis could explain the memory-belief also on lines of association and habit, but the causes of beliefs are obscure, and we cannot investigate them yet. For the present we must content ourselves with the fact that the memory-image can be explained by habit. As regards the memory-belief, we must, at least provisionally, accept Bergson's view that it cannot be brought under the head of habit, at any rate when it first occurs, i.e. when we remember something we never remembered before.

We must now consider somewhat more closely the content of a memory-belief. The memory-belief confers upon the memory-image something which we may call "meaning;" it makes us feel that the image points to an object which existed in the past. In

- W. S. McCulloch and W. Pitts, "A logical calculus of the ideas immanent in nervous activity," The bulletin of mathematical biophysics, vol. 5, no. 4, pp. 115-133, **1943**.

LITERATURE

Carnap, R. 1938. *The Logical Syntax of Language*. New York: Harcourt, Brace and Company.

Hilbert, D., und Ackermann, W. 1927. *Grundüge der Theoretischen Logik*. Berlin: J. Springer.

Russell, B., and Whitehead, A. N. 1925. *Principa Mathematica*. Cambridge: Cambridge University Press.

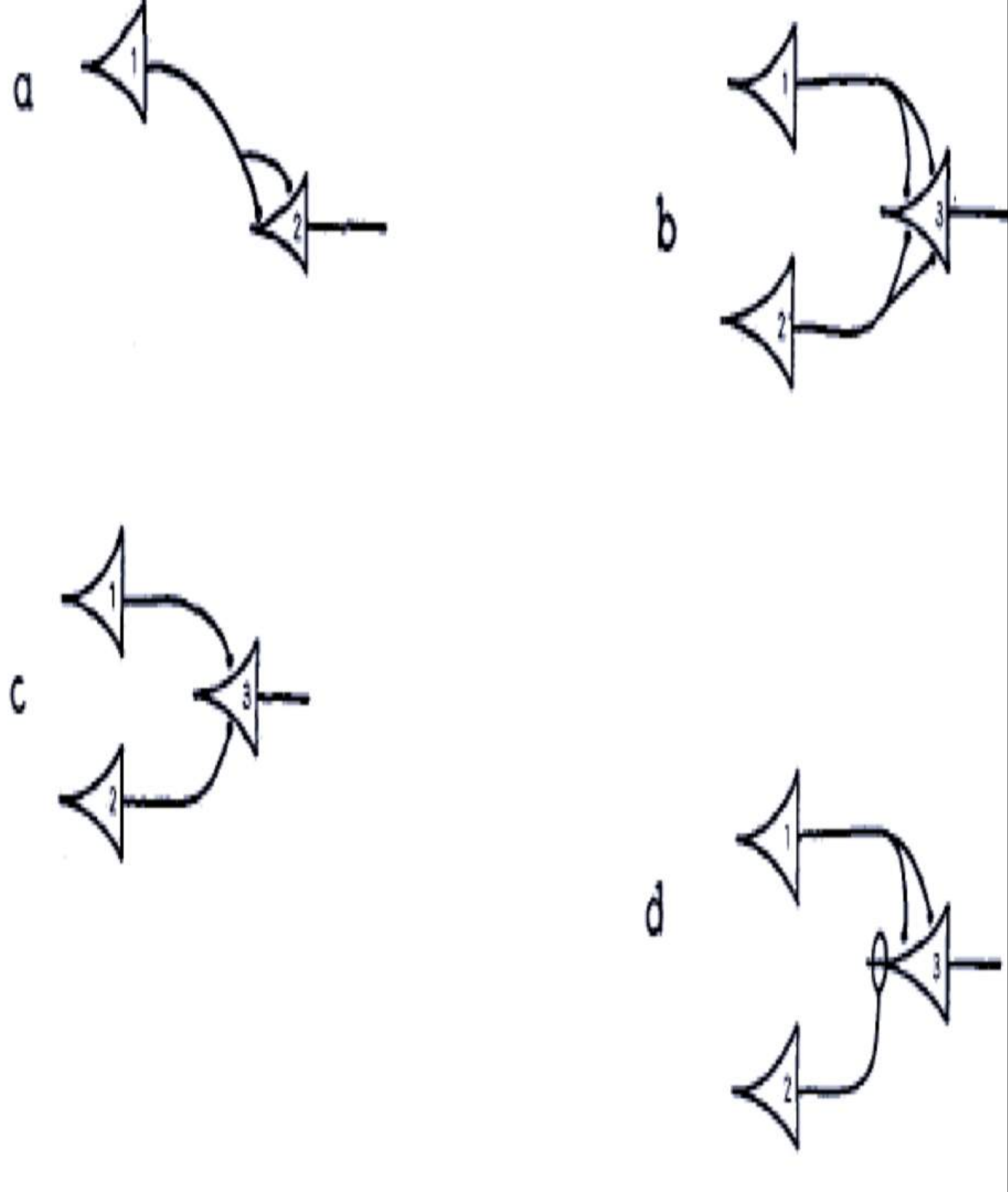
BULLETIN OF
MATHEMATICAL BIOPHYSICS
VOLUME 5, 1943

A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY

WARREN S. MCCULLOCH AND WALTER PITTS

FROM THE UNIVERSITY OF ILLINOIS, COLLEGE OF MEDICINE,
DEPARTMENT OF PSYCHIATRY AT THE ILLINOIS NEUROPSYCHIATRIC INSTITUTE,
AND THE UNIVERSITY OF CHICAGO

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.



- F. Rosenblatt, "The perceptron: a probabilistic model for information storage and organization in the brain." Psychological review, vol. 65, no. 6, p. 386, **1958.**

chines and men included, may eventually be understood.

REFERENCES

1. ASHBY, W. R. *Design for a brain.* New York: Wiley, 1952.
2. CULBERTSON, J. T. *Consciousness and behavior.* Dubuque, Iowa: Wm. C. Brown, 1950.
3. CULBERTSON, J. T. Some uneconomical robots. In C. E. Shannon & J. McCarthy (Eds.), *Automata studies.* Princeton: Princeton Univer. Press, 1956. Pp. 99–116.
4. ECCLES, J. C. *The neurophysiological basis of mind.* Oxford: Clarendon, 1953.
5. GOLDSTEIN, K. *Human nature in the light of psychopathology.* Cambridge: Harvard Univer. Press, 1940.
6. HAYEK, F. A. *The sensory order.* Chicago: Univer. Chicago Press, 1952.
7. HEBB, D. O. *The organization of behavior.* New York: Wiley, 1949.
8. KLEENE, S. C. Representation of events in nerve nets and finite automata. In C. E. Shannon & J. McCarthy (Eds.), *Automata studies.* Princeton: Princeton Univer. Press, 1956. Pp. 3–41.
9. KÖHLER, W. Relational determination in perception. In L. A. Jeffress (Ed.), *Cerebral mechanisms in behavior.* New York: Wiley, 1951. Pp. 200–243.
10. MCCULLOCH, W. S. Why the mind is in the head. In L. A. Jeffress (Ed.), *Cerebral mechanisms in behavior.* New York: Wiley, 1951. Pp. 42–111.
11. MCCULLOCH, W. S., & PITTS, W. A logical calculus of the ideas immanent in nervous activity. *Bull. math. Biophysics,* 1943, **5**, 115–133.
12. MILNER, P. M. The cell assembly: Mark II. *Psychol. Rev.,* 1957, **64**, 242–252.
13. MINSKY, M. L. Some universal elements for finite automata. In C. E. Shannon & J. McCarthy (Eds.), *Automata studies.* Princeton: Princeton Univer. Press, 1956. Pp. 117–128.
14. RASHEVSKY, N. *Mathematical biophysics.* Chicago: Univer. Chicago Press, 1938.
15. ROSENBLATT, F. *The perceptron: A theory of statistical separability in cognitive systems.* Buffalo: Cornell Aeronautical Laboratory, Inc. Rep. No. VG-1196-G-1, 1958.
16. UTTLEY, A. M. Conditional probability machines and conditioned reflexes. In C. E. Shannon & J. McCarthy (Eds.), *Automata studies.* Princeton: Princeton Univer. Press, 1956. Pp. 253–275.
17. VON NEUMANN, J. The general and logical theory of automata. In L. A. Jeffress (Ed.), *Cerebral mechanisms in behavior.* New York: Wiley, 1951. Pp. 1–41.
18. VON NEUMANN, J. Probabilistic logics and the synthesis of reliable organisms from unreliable components. In C. E. Shannon & J. McCarthy (Eds.), *Automata studies.* Princeton: Princeton Univer. Press, 1956. Pp. 43–98.

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Psychological Review
Vol. 65, No. 6, 1958

THE PERCEPTRON: A PROBABILISTIC MODEL FOR INFORMATION STORAGE AND ORGANIZATION IN THE BRAIN[1]

F. ROSENBLATT

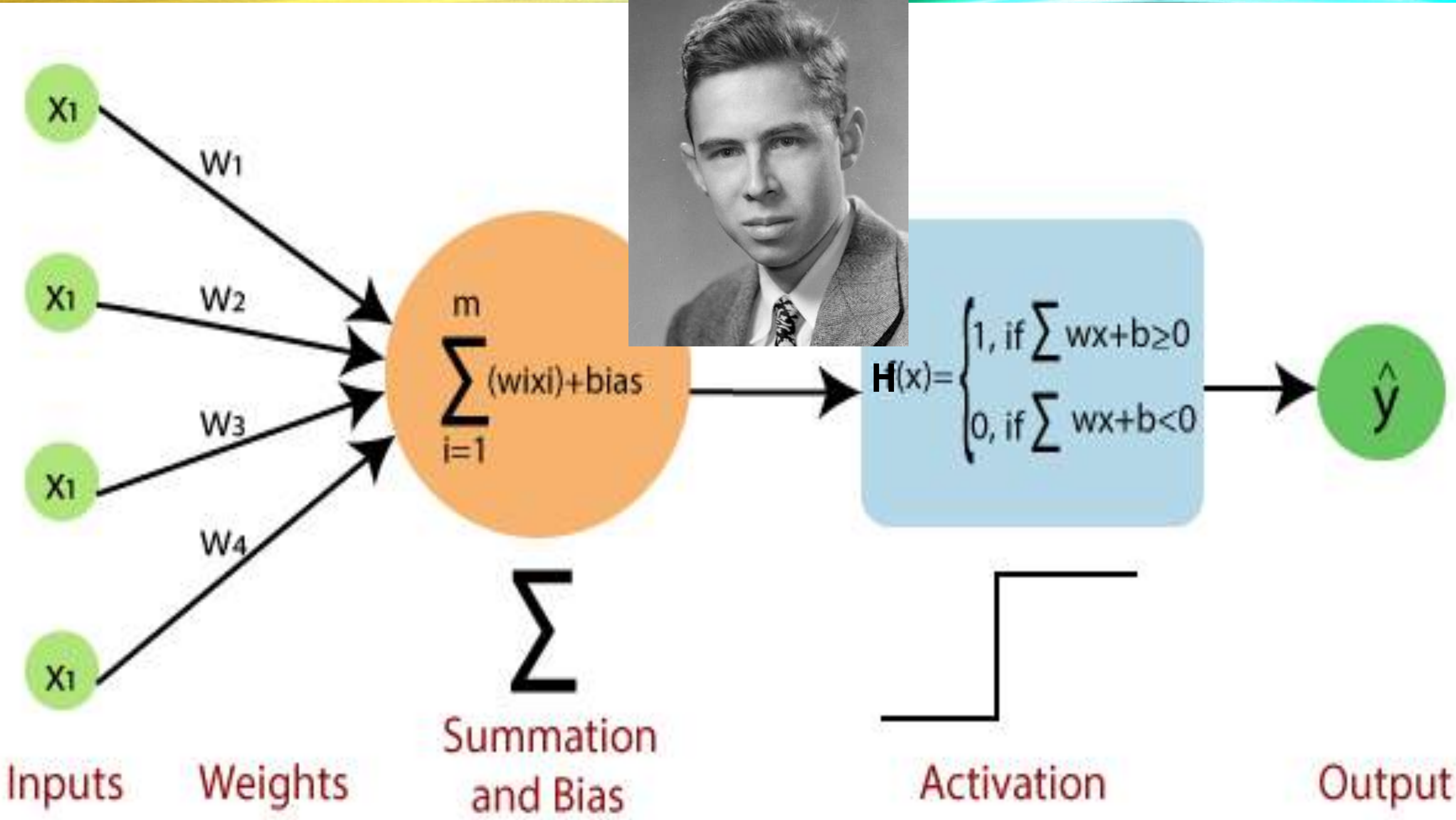
Cornell Aeronautical Laboratory

If we are eventually to understand the capability of higher organisms for perceptual recognition, generalization, recall, and thinking, we must first have answers to three fundamental questions:

1. How is information about the physical world sensed, or detected, by the biological system?
2. In what form is information stored, or remembered?
3. How does information contained in storage, or in memory, influence recognition and behavior?

The first of these questions is in the province of sensory physiology, and is the only one for which appreciable understanding has been achieved. This article will be concerned primarily with the second and third questions, which are still subject to a vast amount of speculation, and where the few relevant facts currently supplied by neurophysiology have not yet been integrated into an acceptable theory.

With regard to the second question, two alternative positions have been maintained. The first suggests that storage of sensory information is in the form of coded representations or images, with some sort of one-to-one mapping between the sensory stimulus and the stored pattern. According to this hypothesis, if one understood the code or "wiring diagram" of the nervous system, one should, in principle, be able to discover exactly what an organism remembers by reconstructing the original sensory patterns from the "memory traces" which they have left, much as we might develop a photographic negative, or translate the pattern of electrical charges in the "memory" of a digital computer. This hypothesis is appealing in its simplicity and ready intelligibility, and a large family of theoretical brain models has been developed around the idea of a coded, representational memory (**2**, **3**, **9**, **14**). The alternative approach, which stems from the tradition of British empiricism, hazards the guess that the images of stimuli may never really be recorded at all, and that the central nervous system simply acts as an intricate switching network, where retention takes the form of new connections, or pathways, between centers of activity. In many of the more recent developments of this position (Hebb's "cell assembly," and Hull's "cortical anticipatory goal response," for example) the "responses" which are associated to stimuli may be entirely contained within the CNS itself. In this case the response represents an "idea"



x1
x1
x1
x1
w1
w2
w3
w4
$\sum_{i=1}^{m}$ (wixi)+bias
H(x)= 1, if ∑ wx+b≥0
0, if ∑ wx+b<0
ŷ
∑
Inputs
Weights
Summation and Bias
Activation
Output

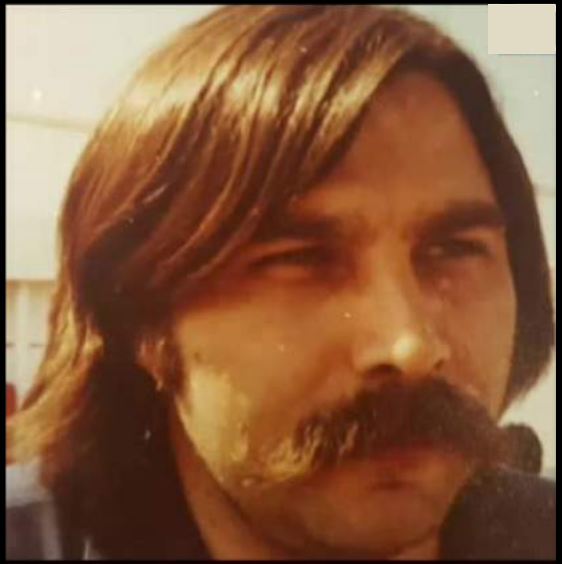
ERIC GOLES CHACC CAREER

University of Chile	1970-1975	Engineer
Catholic University	1972-1973	Studies in Philosophy
University of Grenoble (France)	1977-1980	Ph.D. in Engineering (Computer Science)
University of Grenoble (France)	1985	Ph.D. in Mathematics (Docteur d'Etat)

University of Chile - Deparment Mathematic Engineering	Professor	1974 – 2006
University Adolfo Ibañez		(2006 -)
C.N.R.S. France	Researcher	1981 – 1986
	Directeur de Recherche classe exceptionnelle (DRCE)	(2003 -)

National Center for Mathematical Modeling	Director	1997 – March 2000
National Commission for Scientific and Techonological Research (CONICYT)	President	March 2000 – March 2006
Institute for Complex Systems (Valparaíso)	Director Scientific	2003 – up day

GRENOBLE IMAG



J. R. Abrial, Manuel du langage Z (Z/13). Technical report, Electricité De France, 1977.
J.R. Abrial and S. Hallerstede, "Refinement, decomposition, and instantiation of discrete models: Application to Event-B," Fundam. Inf., 77, 1-28, 2007.

F. Robert, "Théorèmes de Perron-Frobenius et Stein-Rosenberg booléens," Linear Algebra and its Applications, 19, 237-250, 1978.
F. Robert, Discrete Iterations: a metric study, Springer, Berlin, 1986.

ERIC GOLES 1ST PAPERS

- 1. Periodic bellavior of generalized threshold functions, in Discrete Math., 30, 1980 (with J. Olivos).
- 2. Comportement it ratif des fonctions a multiseuil, in Inf. and Control, 45, 1980 (with J. Olivos).
- 3. Irerations des fonctions   seuil sur un graphe, in Actes Coll. Cerisy, 'Regards sur la Th orie des Graphes',Presses Pol. Romandes, 1980 (with J. Olivos).
- 4. Etude dynamique des certains modèles de contrôle génétique, in Biométrie et Génétique, Legay et. al. eds., 1980 (with Snoussi E.).
- 5. Comportement periodique des fonctions   seuil binaires, in Disc. Applied Maths., 3, 1981 (with J.Olivos).
- 6. The convergence of symmetric threshold automata, in Inf. and Control, Vol. 51, Nov. 1981 (with J.Olivos).
- 7. A Short proof on the cyclic behaviour of multithreshold symmmetric automata, in Inf. and Control, Vol. 51. 1981, pp. 95-97 (with S. Mart nez).
- 8. Sequential iteration of threshold functions, numerical method in the study of critical phenomena, Della Dora, Demongeot & Lacolle eds., Springer Series in Synergetics, pp. 64-70, Springer Verlag, 1981.
- 9. Fixed point of threshold functions on a finite set, in SIAM Journal on Algebraic and Discrete Vol. 3. No. 4. 1982.
- 10. Specific roles of different Boolean mappings in random networks, in Bull. of Math. Biol., Vol. 44, 1982 (with F. Fogelman, G. Weisbuch).
- 11. Iterative behaviour of generalized majority functions, in Math.Social Sciences, 4, 1983 (with M.Tchuente).

ERIC GOLES 1ST PAPERS

- 12. Transsient length in sequential interations of threshold functions, in Disc. Applied Maths., 6, 1983 (with F.Fogelman, G.Weisbuch).
- 13. Iterative behaviour of one dimensional threshold automata, in Disc. Applied Maths., 8, 1984 (with M.Tchuente).
- 14. Dynamique d'un automate à mémoire modélisant le fonctionnement d'un neurone, Comptes Rendus Acad. Sciences France, t299, S rie I, No. 10, 1984 (with M. Cosnard, presented by R.Thom).
- 15. Dynamical behavior of neural networks, in SIAM Journal on Alg. and Discr. Methods, Vol. 6, No. 4, 1985.
- 16. Erasing multithreshold automata in Dynamical Systems and Cellular Automata, Demongeot et al. Eds., Acad. Press 1985. pp. 47-55 (with M. Tchuente).
- 17. Dynamics on positive automata networks, in Theoretical Computer Sciences, 41 pp. 19-32, 1985.
- 18. Comportement dynamique d'un automate à mémoire, in Actes Coll. Biol. Théorique, Solignac, Benchetrit & Demongeot Eds. CNRS. 1985 (with M. Cosnard).
- 19. The energy as a tool for the study of threshold networks, in Discrete Applied Maths., 12, pp 261-277,1985 (with F. Fogelman).
- 20. Comportement dynamique des réeaux d'automates, Thèse de Doctorat ès Sciences Mathématiques, Grenoble, 1985

E. Goles genealogy

- E. Goles
- F. Robert
- N. Gastinel
- J. Kuntzmann
- G. Valiron (also advisor of L. Schwartz, himself advisor of J.L. Lions)
- E. Borel
- G. Darboux (also advisor of H. Lebesgue)
- M. Chasles
- S.D. Poisson

• J.L. Lagrange (also advisor of J. Fourier)	P.S. Laplace
• L. Euler	J. Le Rond d'Alembert
• Johann Bernoulli (also advisor of D. Bernoulli)	
• Jacob Bernoulli	N. Eglinger
• N. Malebranche	
• G.W. Leibniz	
• C. Huyghens	E. Weigel
• F. van Schooten	J.J. Stampioen
• J. Golius	M. Mersenne (also advisor of B. Pascal)
• W. Snellius	T. Erpenius
• R. Snellius	J.J. Scaliger
• V. Naibod	A. Turnèbe
• E. Reinhold	J. Toussain
• J. Milich	G. Budé
• D. Erasmus	

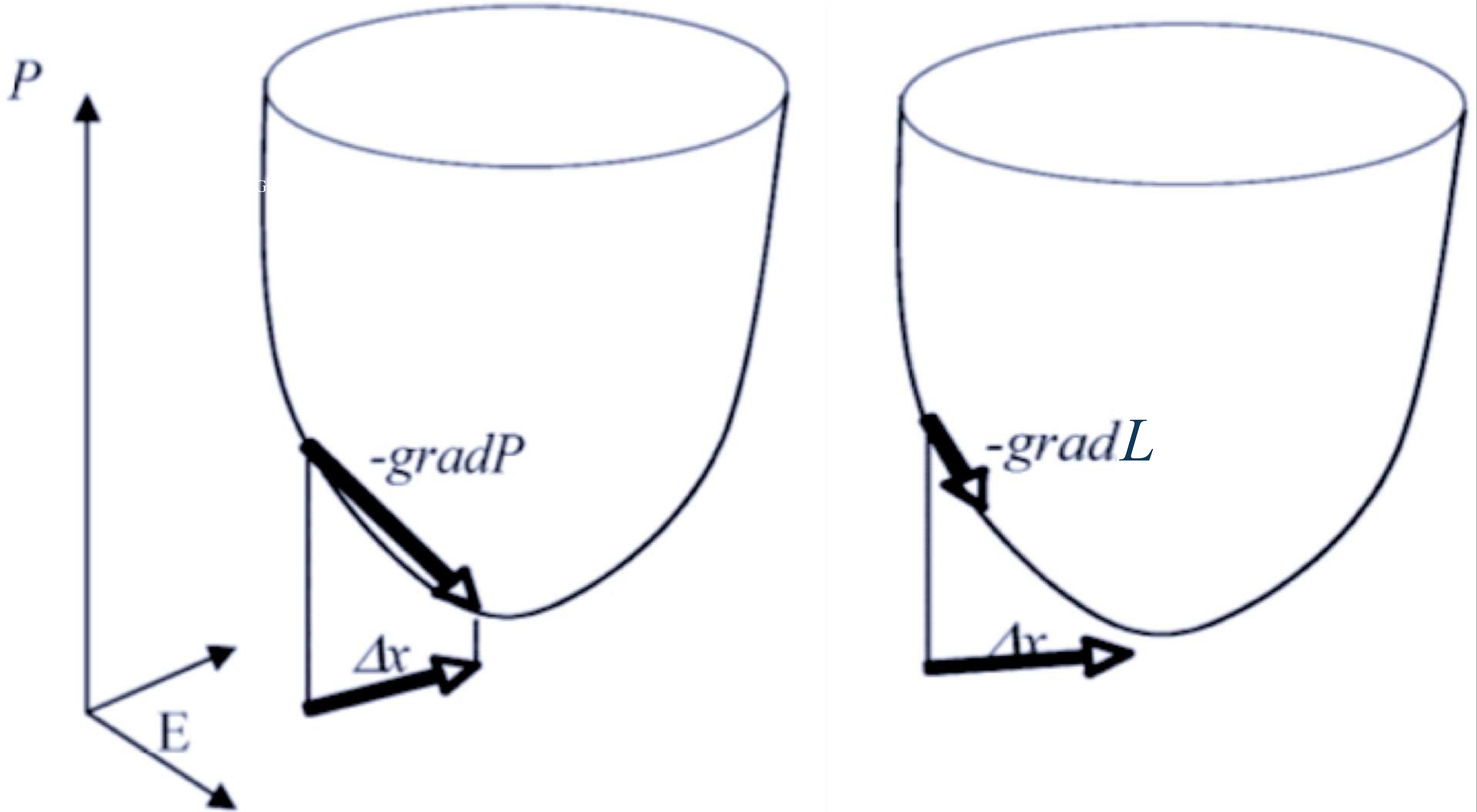
7 BOOLEAN STORIES RELATED TO ERIC

1 POTENTIAL NETWORKS

- ***Proposition 1***

In the Boolean case, let suppose that $A=0$, $P(x)={}^{t}xAx+Bx$, with $a_{ii}=0$ and each sub-matrix on any subset J of indices in $\{1,...,n\}$ of A is non positive and less than the linear operator $(-B)$ restrained on J. Then P decreases on the trajectories of the potential automata defined by $x_i(t+1) = H(-\Delta P/\Delta x_i+x_i(t))$ for any mode of implementation of the dynamics (sequential, block sequential and parallel). These Boolean automata constitute a Hopfield-like network whose weights are $w_{ij} = 1$ and $w_{ij} = - a_{ij} - a_{ji}$, $\forall\ j \neq i$, thresholds are the b_i's, and stable fixed configurations correspond to the minima of P.

- Cosnard, M., Goles E.: Discrete states neural networks and energies. Neural Networks 10, 327-334 (1997).


P
E
-gradP
Δx
-gradL
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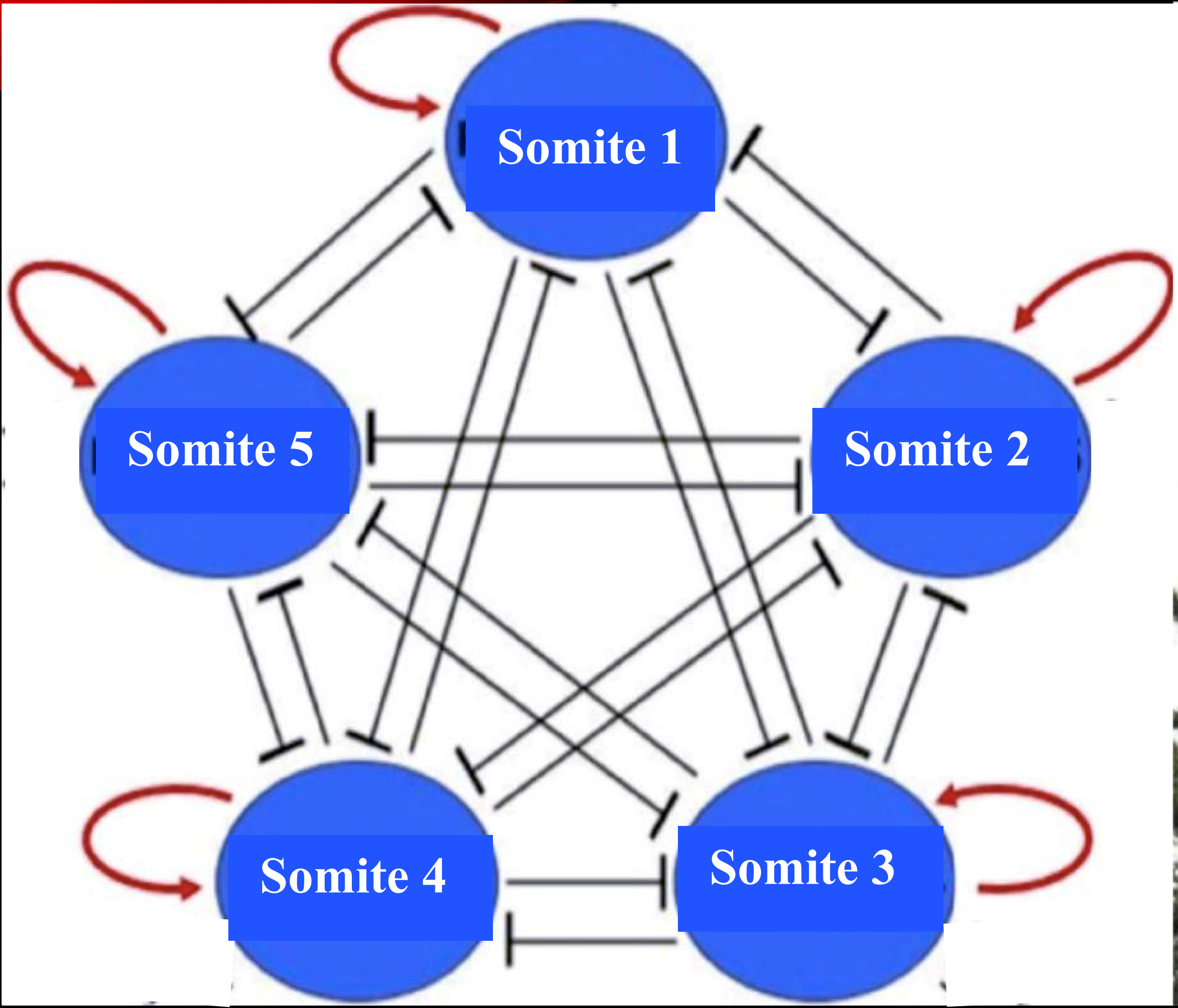

Somite 1
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Somite 5

2 HAMILTONIAN NETWORKS

- ***Proposition 2***

Let us consider a deterministic Hopfield-like network of size *n*, which is a necklace circuit sequentially or synchronously updated with constant absolute value w for its non-zero interaction weights. Then, its dynamics is conservative, keeping constant on the trajectories the Hamiltonian function L defined by:

$$\mathbf{L}(x(t)) = \sum_{i=1,n} \frac{(x_i(t) - x_i(t-1))^2}{2} = \sum_{i=1,n} \frac{H(w_{i(i-1)modn} x_{i-1}(t-1) - x_i(t-1))^2}{2}$$

where *H* denotes the classical Heaviside function. L(x(*t*)) is the total discrete kinetic energy of the network, equal to the half of the global dynamic frustration:

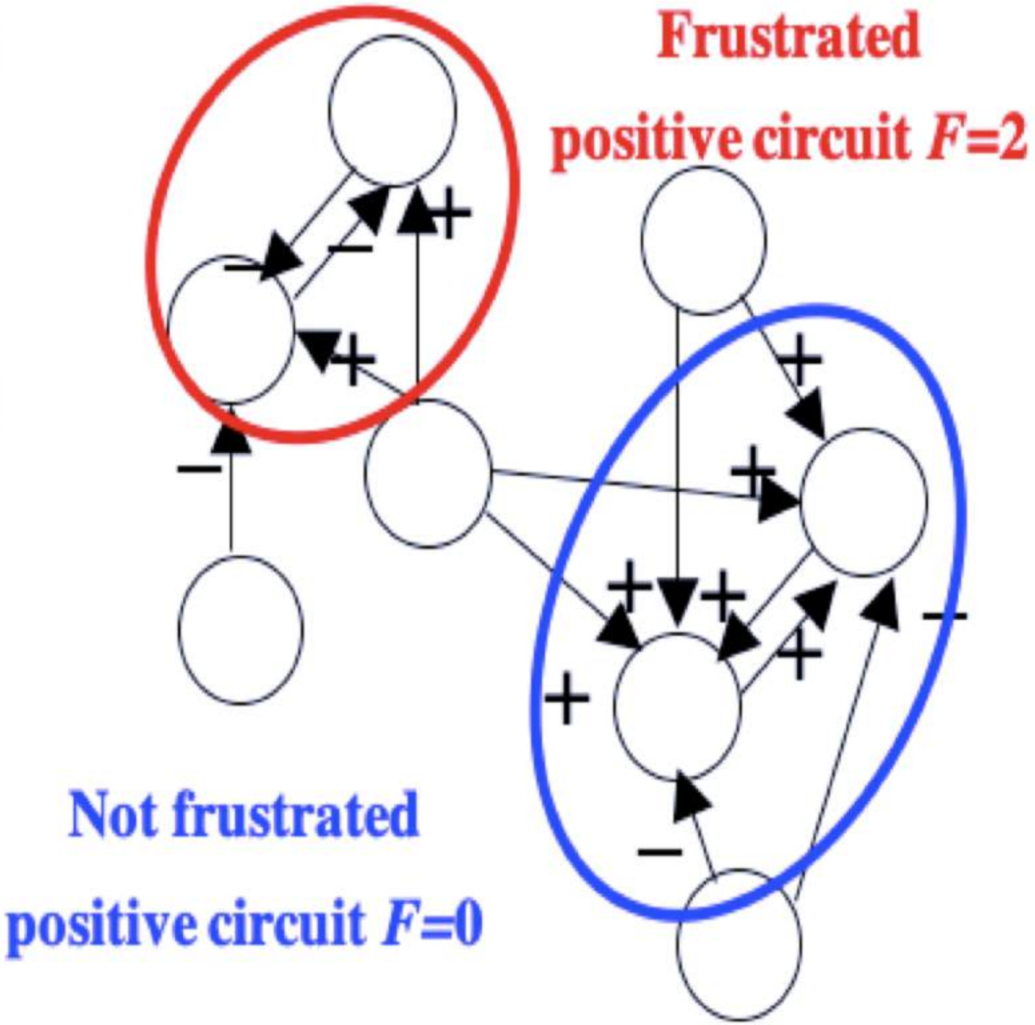
$$F(x(t)) = \sum_{i=1,n} F_{i,(i-1)\text{modn}}(x(t)),$$

- with $F_{i,(i-1)\text{modn}}$ is the local dynamic frustration defined between nodes (*i*−1) and *i* by:

- $F_{i,(i-1)}(x(t))=1$, if $\{\text{sign}(w_{i(i-1)}) = 1 \wedge x_i(t) \neq x_{i-1}(t\text{-}1)\} \vee \{\text{sign}(w_{i(i-1)}) = \text{-}1 \wedge x_i(t) = x_{i-1}(t\text{-}1)\}$,

  =0, if not.

F Global frustration	Configuration Nb	Attractor Nb	Attractor Length
0	1	2 fixed points	1
2	$4 = C_{n-H+2}^{H-1}/2$	7	8
4	$10 = C_{n-H+2}^{H-1}/2$	3	4 (symmetrized)
4		16	8
6	$4 = C_{H+2}^{n-H-1}/2$	7	8
8	1	1	2



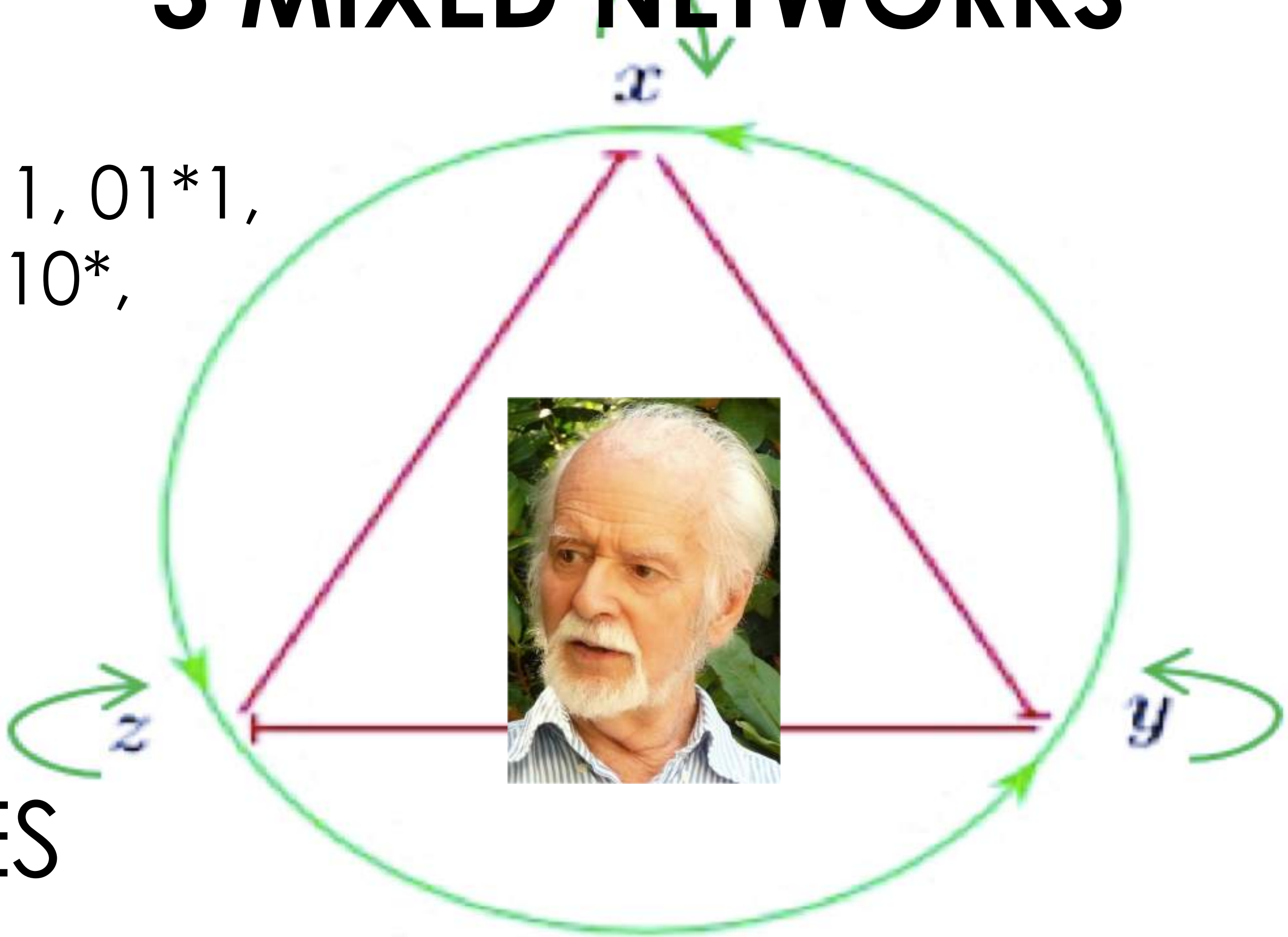
E. Goles, F. Fogelman-Soulié, D. Pellegrin. Decreasing energy functions as a tool for studying threshold networks. *Discrete Applied Mathematics,* 12, 261-277 (1985).

J. Demongeot, H. Ben Amor, P. Gillois, M. Noual & S. Sené Robustness of regulatory networks. A Generic Approach with Applications at Different Levels: Physiologic, Metabolic and Genetic.*Int. J. Molecular Sciences*, **10**, 4437-4473 (2009).

3 MIXED NETWORKS

2 unstable fixed points (000), (111)

1 stable cycle of order 6 (010*, 0*11, 01*1, 001*, 0*01, 10*1, 101*, 1*00, 10*0, 110*, 1*10, 01*0)



R. THOMAS ARABESQUES

Boolean equations of such a system of size *n* is given by:

$$\forall i=1,\ldots,n,\ x_i = H(w_{ii}\, x_i - w\, x_{i+1(mod n)} + w\, x_{i-1(mod n)})$$

C. Antonopoulos, V. Basios, J. Demongeot, P. Nardone, R. Thomas Linear and nonlinear arabesques: a study of closed chains of negative 2-element circuits. *Int. J. Bifurcation and Chaos*, **23**, 9, 30033 (2013).

4 SOCIAL NETWORKS

In the spirit of the games theory of the seventies [12], Eric Goles and Maurice Tchuente considered in [13] a society of n persons {P1,…,Pn} having at time t opin-ions {x1(t),…, xn(t)} with interaction coefficient aij = aji between Pi and Pj. Let {θ1,…,θp} be the set of possible opinions which may be assumed by any person, with a local hierarchy hi adopted by each person Pi (a reordering of opinion indices without ex-æquo, that is a permutation of {1,…, p}). The dynamical behaviour of such a society depends on local majority rules, where, if a(k) denotes the global weight of the opinion θk, the change of opinion is made as follows:

$$xi(t+1) = k, \text{ with } k = \sup\{i \ / \ \forall r=1,...,p,\ a(i)\Sigma_{j/xj(t)=k}\, aij \geq a(r)\Sigma_{j/xj(t)=r}\, aij\}$$

- ***Proposition 3***

In such a society the opinion of any member Pi, after a certain number of steps, either remains constant or oscillates between two values.

E.Goles, M. Tchuente. Iterative behaviour of generalized majority functions. *Math. Social Sciences* 4, 197-204 (1983).

J. Demongeot, V. Volpert. Dynamical System Model of Decision Making and Propagation. *J. Biol. Systems*, 23, 339-353 (2015).

M. Banerjee, J. Demongeot & V. Volpert. Global Regulation of Individual Decision Making. *Mathematical Methods in the Applied Sciences*, 39, 4428-4436 (2016).

5 DISCRETE CONVOLUTION FOR DEEP LEARNING

- The Boolean automata $z(t)$ resulting from the discrete convolution between two Boolean automata $x(t)$ and $y(t)$ (called the kernel filter) can be defined as follows:

$$z_i(t) = \Sigma_{i-k\in V(i)}\ x_{i-k}(t)\ y_k(t)$$

where the size of the neighbourhood $V(i)$ equals p and the positive kernel filter of size p, $y(t)$, verifies: for any t, $\Sigma_{k=1,p}\, y_k(t) = 1$. If $x(t)$ has a regular derivative (in the sense of F. Robert), that is, for any spatial derivative and any t, $\Sigma_{j=1,p} |\Delta x_j(t)/\Delta j| \leq 1$, then $z(t)$ is also regular, because we have: $\Sigma_{j=1,p} |\Delta z_j(t)/\Delta j| \leq \Sigma_{j=1,p}\Sigma_{j-k\in V(j)} |\Delta x_{j-k}(t)/\Delta k|\, y_k(t) \leq 1$.

le *Cun*, Y. Learning processes in an asymmetric threshold network. In: Fogelman-Soulié, F., Bienenstock, E., Weisbuch, G. (eds.) Disordered systems and biological organization, *Les Houches*, 1985, pp. 233-240, North Holland, Amsterdam (1986).

6 BLOCK PARALLEL UPDATING

- A good example of application for a new updating mode is the nuclear and mitochondrial genetic expression in which the combination of cellular repressors (microRNAs and circular RNAS), mitochondrial genes (relative to the cell respiration) and nuclear genes under the control of the chromatin clock, present a dynamical schedule close to a new updating mode called block-parallel, for which the updating is sequential inside blocks, these blocks being updated parallelly with not necessary the same internal clock.

J. Demongeot & S. Sené About block-parallel Boolean networks: a position paper. *Natural Computing*, **19**, 5-13 (2020).

7 Coupled neural networks

- Interactions between two Boolean automata of size 2, one with transition F_0 and the other with transition G_0, evolving in time with the following rules, where symbol ¬ denotes Boolean complementary (negation):

- - Sequential dependence: $G_1(x_1, x_2)=G_0(F_0(x_1, x_2), x_2)$, $F_1(x_1, x_2)=F_0(x_1, G_1(x_1, x_2))$,…, $G_i(x_1, x_2) = G_{i-1}(F_0(x_1, x_2), x_2)$, $F_i (x_1, x_2) = F_{i-1} (x_1, G_i(x_1, x_2))$,…
- - Parallel dependence: $G_1(x_1, x_2) = G_0(F_0(x_1, x_2), x_2)$, $F_1(x_1, x_2) = F_0(x_1, G_0(x_1, x_2))$,…,
- $G_i(x_1, x_2) = G_{i-1}(F_0(x_1, x_2), x_2)$, $F_i (x_1, x_2) = F_{i-1} (x_1, G_{i-1}(x_1, x_2))$,…
- - Sequential opposition: $G_1(x_1, x_2)=G_0(\neg F_0(x_1, x_2), x_2)$, $F_1(x_1, x_2)=F_0(x_1, \neg G_1(x_1, x_2))$,…, $G_i(x_1, x_2) = G_{i-1}(\neg F_0(x_1, x_2), x_2)$, $F_i (x_1, x_2) = F_{i-1} (x_1, \neg G_i(x_1, x_2))$,…
- - Parallel opposition: $G_1(x_1, x_2) = G_0(\neg F_0(x_1, x_2), x_2)$, $F_1(x_1, x_2) = F_0(x_1, \neg G_0(x_1, x_2))$,…,
- $G_i(x_1, x_2) = G_{i-1}(\neg F_0(x_1, x_2), x_2)$, $F_i (x_1, x_2) = F_{i-1} (x_1, \neg G_{i-1}(x_1, x_2))$,…

Eberhard-Robert scholia

Proposition 4

i) Sequential and parallel dependence (resp. opposition) rules give same fixed points.

ii) The transform by sequential (resp. parallel) opposition of $(\neg F, \neg G)$ is the complementary of the transform by sequential (resp. parallel) dependence of (F, G).

Such a result can be applied to situations in which two groups of actors (political, ethnic, social, neural, genetic, etc.) or two age classes evolve by taking social choices with cross interactions. It could serve namely to revisit and interpret the asymptotic properties of complex Boolean biological network.

F. ROBERT

- « Mon billet pour Éric », by François Robert

- « Éric, la scène se passe à Grenoble quelques années après ta soutenance de thèse. Retour d'Israël via Paris, et avant de rentrer à Santiago, tu débarques impromptu ce matin-là dans mon bureau de la Tour IRMA au Campus. Nous sommes contents de nous revoir, et tu commences à m'expliquer au tableau ce qui préoccupe ton esprit en ce moment. S'agissait-il du tas de sable qui s'effondre sur lui-même ? Je crois que oui. Et tu me montres la relation mathématique que tu as écrite au tableau : « Tu vois, cette expression, eh bien elle ne me plaît pas, elle n'est pas casher ! » Devant mon air d'incompréhension, tu corriges immédiatement : « Disons qu'elle n'est pas très catholique ! », ce qui n'a pas amélioré ma compréhension pour autant, mais j'ai alors saisi en un éclair le concept de mathématicien international que tu commençais à incarner alors.

- J’ai par ailleurs été très sensible au témoignage chaleureux que tu as rendu récemment à Jacques Demongeot, dans lequel tu insistes beaucoup pour rendre effectivement sensible cette part d’éternité et de globalité de vos échanges dînatoires, mathématiques ou non, que ce soit au Bar national de Santiago ou ailleurs : une caractéristique importante qui vous situe bien. Et de plus, ce témoignage m’a redonné comme instantanément aussi la vive perception du compagnonnage artisanal qui animait les membres de notre groupe « Comportement d’Itérations ».

- Quelle équipe, en effet, d’excellents chercheurs ! Je les cite par ordre d’entrée en scène : Michel Cosnard, Maurice Tchuente, toi Eric, Françoise Fogelman, Houcine Snoussi, Yves Robert, les premiers couteaux en quelque sorte, tous chercheurs C.N.R.S. (sauf Françoise, universitaire, et Houcine, boursier marocain) et une huitaine de jeunes en troisième cycle. Jacques Demongeot entretenait des relations suivies avec tout ce petit monde. Nous partagions chaque semaine notre conviction dans la dimension intemporelle de notre réalité mathématique en cours d’élaboration, assidûment méditée et travaillée, et c’était là que résidait le ciment du groupe.

- En ce qui te concerne, ta façon très spécifique de « faire des maths » est maintenant largement connue : fougueux, jovial, parfois brouillon et fâché de l'être, tu déploies au tableau une puissante séduction mathématique, qui jaillit de ta très forte conviction personnelle, manipulant un maelström de notions entrelacées… Tu convaincs, car tu es habité, et spécifiquement toi !

- Il n'empêche : les deux théorèmes de Golès-Martinez sur les cycles de longueur deux dans les réseaux d'automates à seuils symétriques (il y a trente-cinq ans !) resteront pour moi le signal fort d'un accomplissement à venir, qui s'est grandement réalisé depuis. J'ai même vu récemment que tu avais contribué à faire, de la fourmi de Langton, la brique de base d'un calculateur universel, dans la ligne de ce que vous élaboriez à l'époque avec Maurice Tchuente et Yves Robert sur d'autres modèles…

- Cher Éric, bon et heureux **70**, et longue vie ! Avec toute mon amitié, »

François Robert.