Feedback, sensitivity, and complexity

R. Sepulchre -- University of Cambridge

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Neuroscience in silico: one illustration of complexity (2015)

Reconstruction and Simulation of Neocortical Microcircuitry

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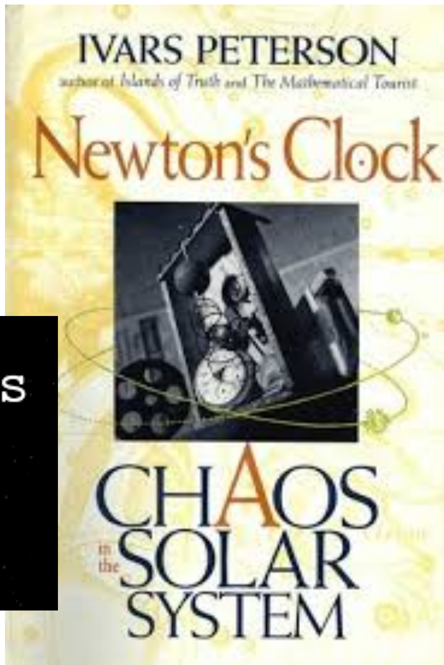
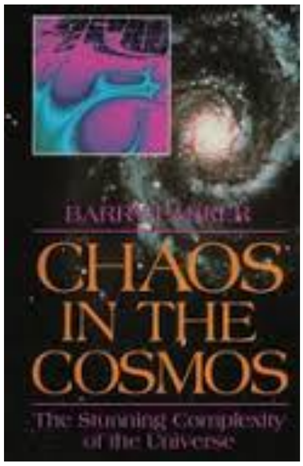
Blue Brain Project

Celestial mechanics:
another illustration of complexity





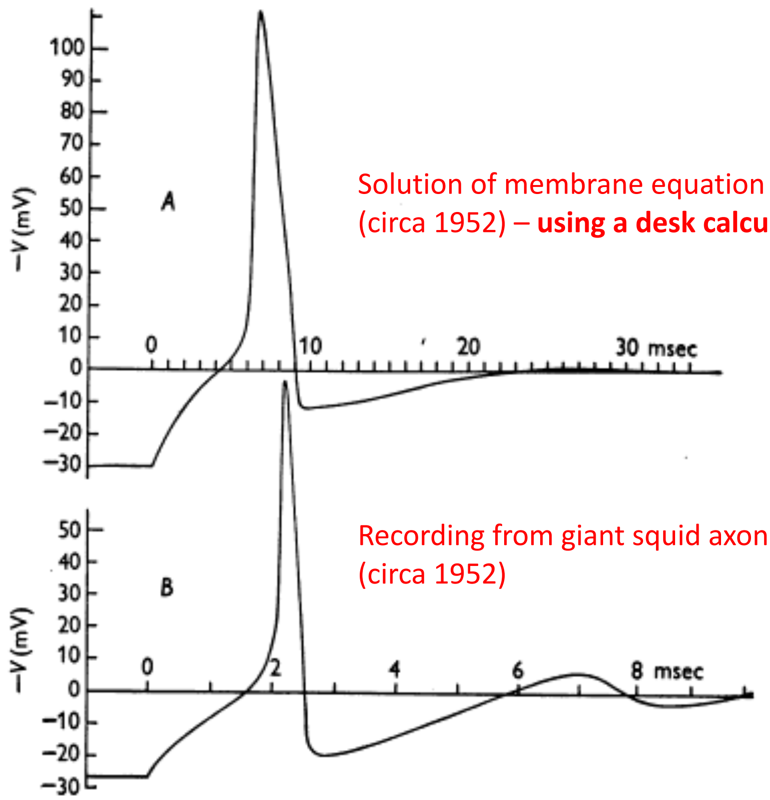
A common theme:
How to model the interconnection between the tiny and the large ?

Lecture 1 : the local and the global. A control theorist viewpoint

Lecture 2 : the complexity of sensitivity analysis across scales

Lecture 3 : a simple paradigm for robust control across scales

Neuronal excitability is **very well understood**



Solution of membrane equation (circa 1952) – **using a desk calculator**!

Recording from giant squid axon (circa 1952)

Hodgkin & Huxley, J Physiol. (1952)

Part I. *The local*

A local anecdote (1990)

Nonlinear control...

"*But science is linear, is'nt?*"

Theme 1 (science)

Local		*global*	
Linear	methods are our only window onto a	*nonlinear*	world.
Simple		*complex*	

A local anecdote (2000)

The essence of feedback ?

"*Feedback linearizes !* "

Theme 2 (engineering)

Zooming principles
are key to
the efficiency of local windows

Two "local" anecdotes (changing the resolution)

A linearization principle

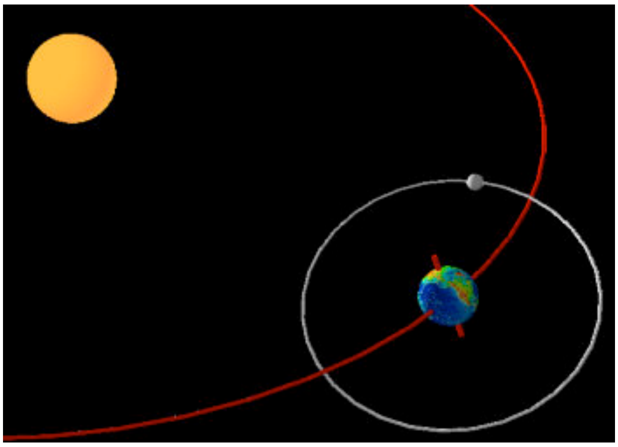
Newton discovered a way of solving any equations (...). He regarded this discovery as his most important achievement (...). (V. I. Arnold)

A zooming principle

Black's patent application for the negative feedback amplifier took some nine years to get approved (...).

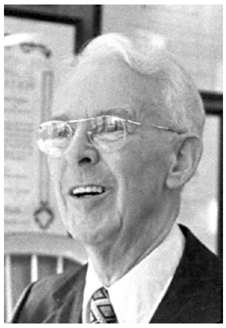
The principle of linearization

Nearby behaviors can be studied by local methods

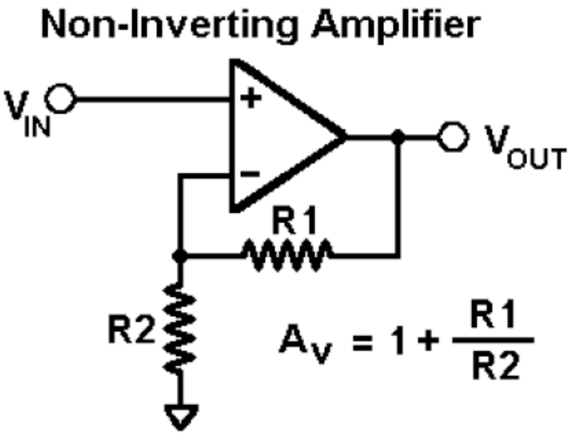


Earth-moon-sun behavior as a nearby behavior of the earth-sun behavior

The feedback principle of localization



Interconnections change the meaning of 'local'



By late 1927, Black's prototype negative feedback amplifier "achieved a distortion reduction of 100,000 to 1 with a frequency range extending from 4 to 45 kHz."

The local

- The linearization principle: nearby behaviors can be studied by linear methods. A foundation of modern science.

- The feedback principle: interconnections change the resolution of local. A foundation of modern engineering.

Part II. *The global*

The world is complex …

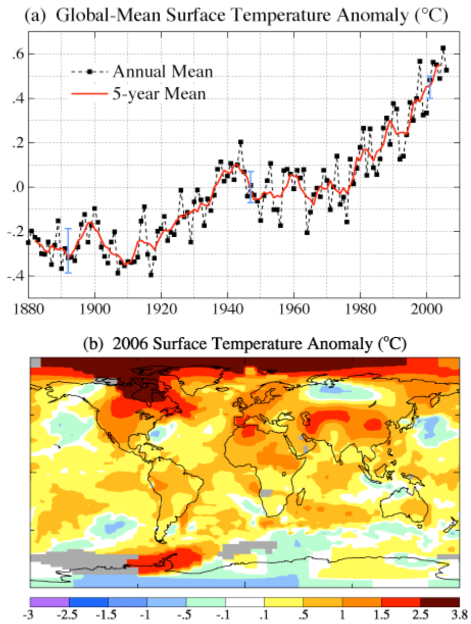
Behaviors: what we wish to understand (through mathematical models)

‘Laws that relate signals’ (J.C. Willems)

Complex behaviors: those that we do not understand (yet)

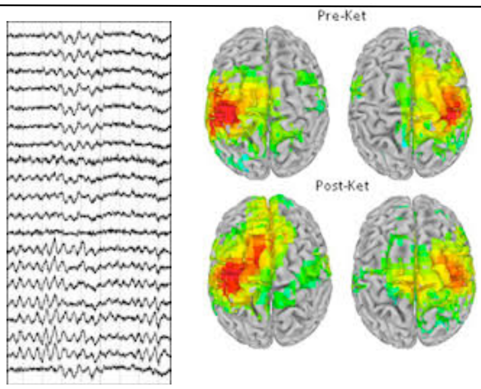
Examples of (complex) behaviors

our economy

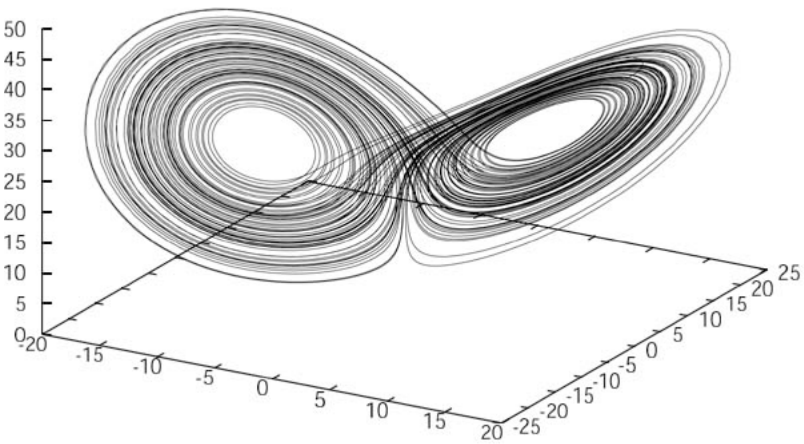


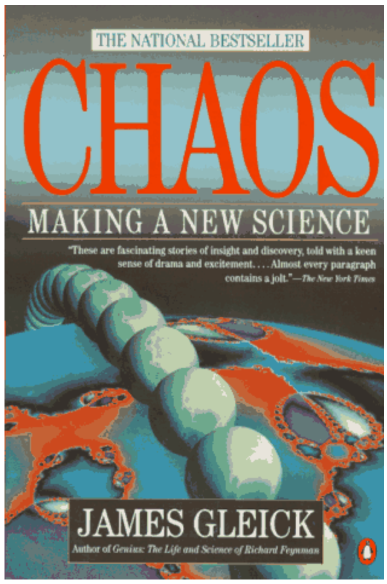
our climate

our brain

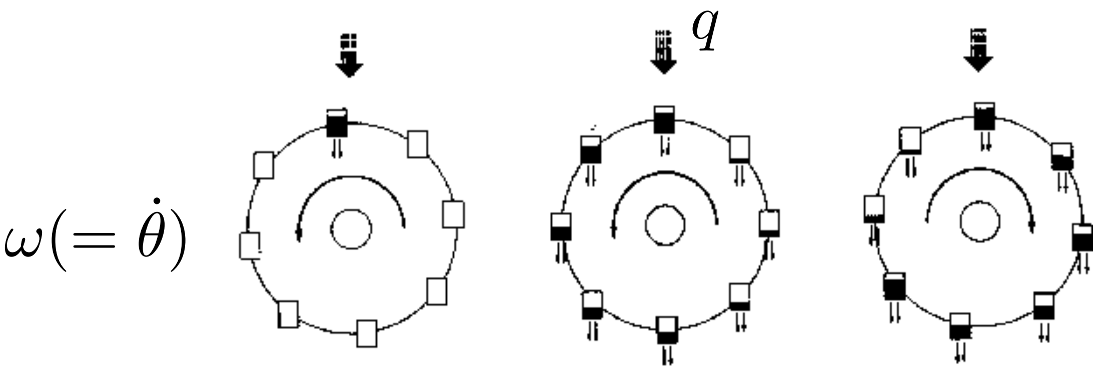


A popular complex behavior for a 1990 engineering student





A hub of complexity in a simple world



Strogatz chaotic water wheel.

$$
\begin{aligned}
I\dot{\omega} &= -\nu\omega + g\,\Re z \\
\dot{z} &= -(K + j\,\omega)z + q
\end{aligned}
$$

A simple ‘exact’ law, yet an unpredictable future

A hub of complexity in a simple world

Simple laws may determine ‘erratic’ behaviors

Enormous impact on the scientific community: quest for the “simple law” that determines “complex behaviors”

(stock markets, heart rate variability, epileptic seizures, positive emotions, ...)

Positive Affect and the Complex Dynamics of Human Flourishing

Barbara L. Fredrickson *University of Michigan*
Marcial F. Losada *Universidade Católica de Brasília*

(American Psychologist, 2005)

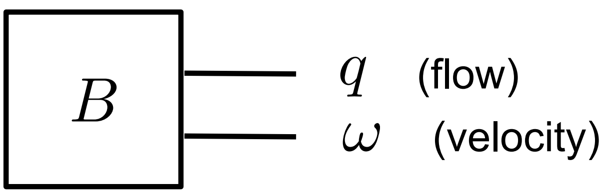
Table 1
Coupled Differential Equations Developed by Losada (1999) to Describe the Differential Performance of Low-, Medium-, and High-Performance Teams

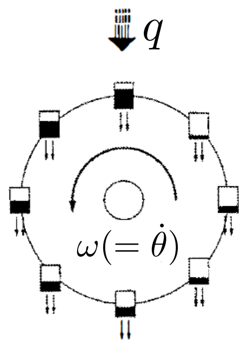
Variable	Differential equation	Constant
X = inquiry–advocacy	$dX/dt = (Z - X)a$	$a = 10$
Y = positivity–negativity	$dY/dt = XZ - bY$	$b = 8/3$
Z = other–self	$dZ/dt = cX - XY - Z$	c = connectivity[a]

Note. The initial conditions are $X_0 = 1$, $Y_0 = 16$, and $Z_0 = 1$. The integration step, Δt, was set to .02. The integration algorithm was Runge–Kutta Order 4.
[a] The control parameter, defined by the number of empirically observed nexi (strong, lasting social connections, as measured by the cross-correlation function). This parameter was set to 18 (the number of nexi) for low-performance teams, 22 for medium-performance teams, and 32 for high-performance teams.

From the abstract: *188 participants (...) provided daily reports of experienced positive and negative emotions over 28 days. Results showed that the mean ratio of positive to negative effect was above 2.9 for individuals classified as flourishing and below that treshold for those not flourisihing.*

The water wheel as an *open* system





Low flow	Medium flow	High flow
Linear behavior	Resonant behavior	Switching behavior
exogenous	sensitive	endogenous

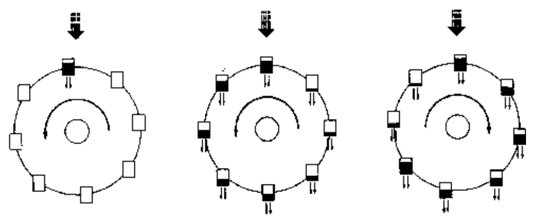
Deterministic chaos

Simple laws may determine ‘erratic’ behaviors

Whether a law and an initial condition are sufficient for *prediction* is a question that can be formulated for *closed* systems only.

Whether a behavior is *sensitive* (or resonant) is a valid question for *open* systems. It does not imply nor require ‘chaos’.

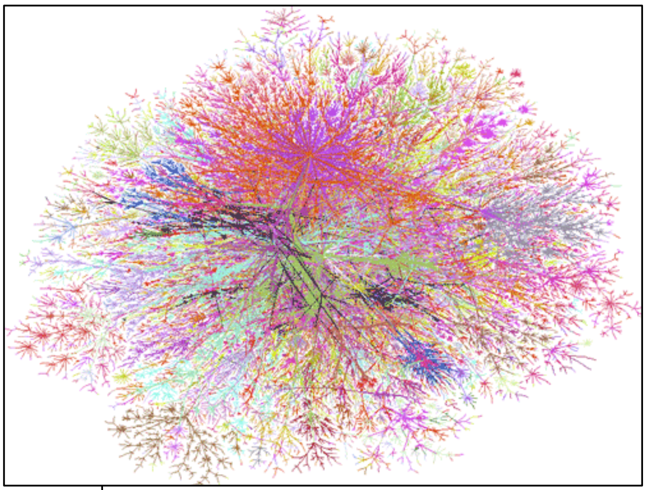
Feedback tunes sensitivity



damping = negative feedback
balances
gravity = positive feedback

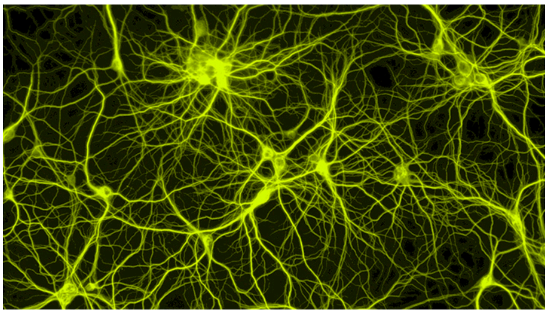
Negative feedback	Balanced feedback	Positive feedback
Linear behavior	resonant behavior	Switching behavior
exogenous	sensitive	endogenous

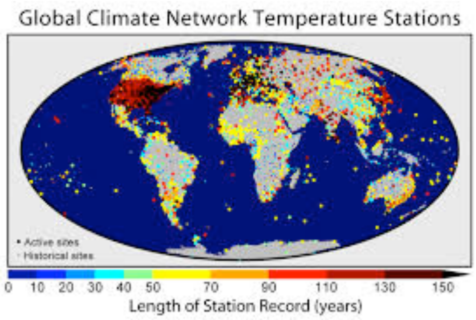
Interconnections: Push for theory of open systems



our economy

our brain





our climate

The global

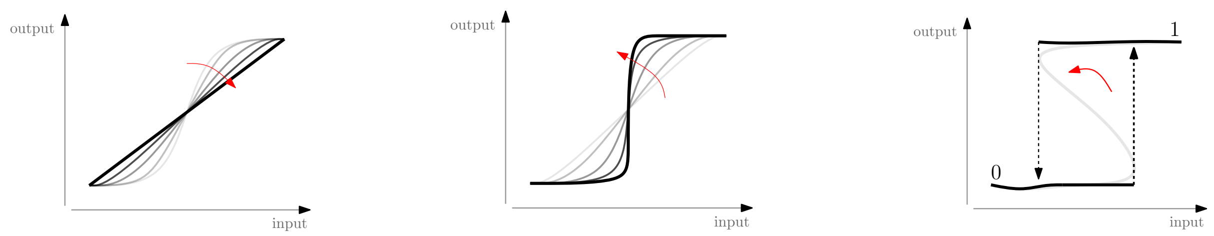
Complexity is a temporary and evolving concept

Behaviors as closed systems	Behaviors as open systems
Laws determine behaviors	Interconnections shape behaviors
Observing our universe	Interacting with our universe
(celestial mechanics)	(global warming; the brain)

Part III. *Encounters*
(local windows on the global)

Feedback glocalizes

Negative feedback balanced by positive feedback



Regulating behaviors

Linear

exogenous

continuous

(feedback zooms out)

sensitivity resonance

(feedback zooms in)

Decision-making behaviors

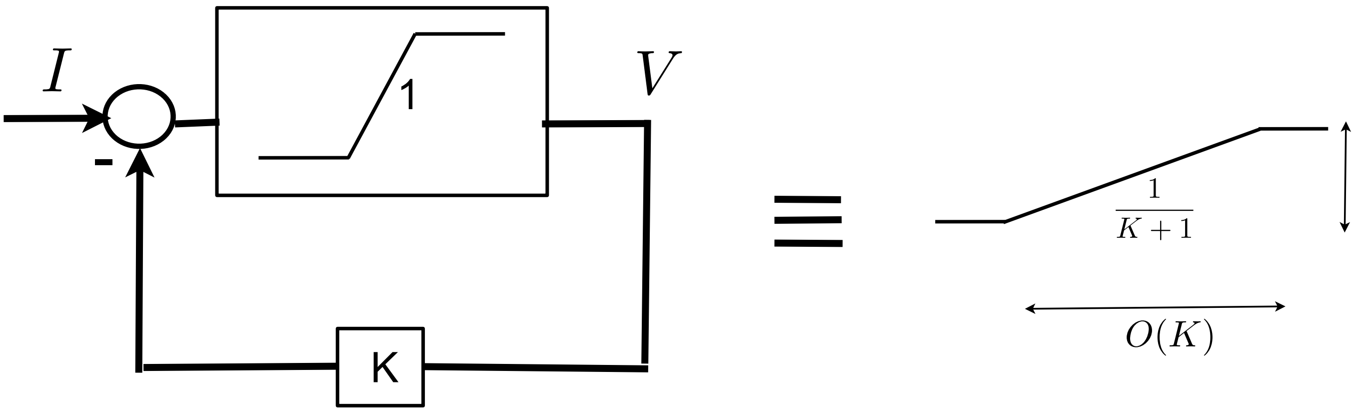
Switch

endogenous

discrete

(feedback zooms out)

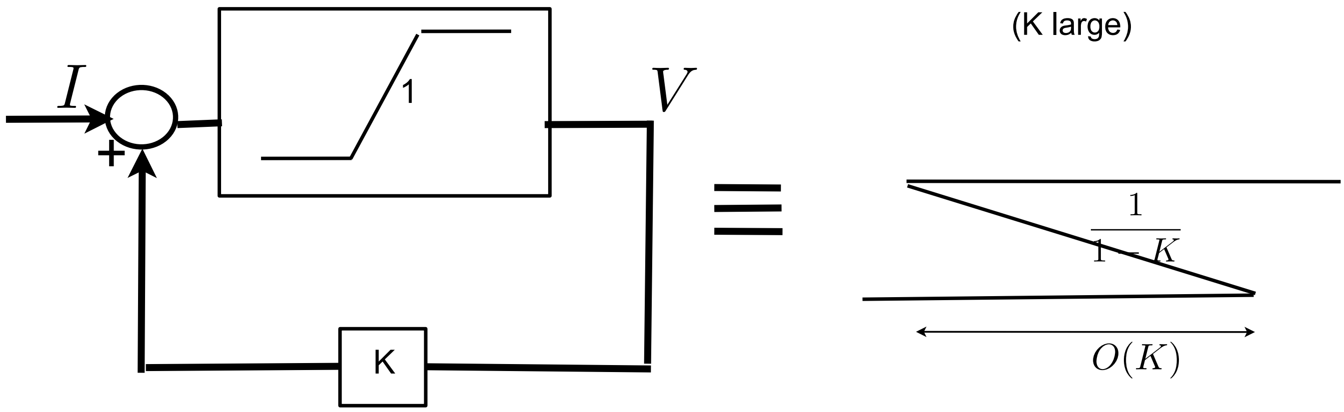
The negative feedback amplifier ‘linearizes’



$$V = \mathrm{sat}_1(I - KV) \quad \equiv \quad V = \mathrm{sat}_{\frac{1}{1+K}}(I)$$

Sensitivity domain is spread by negative feedback
(The essence of control theory)

The positive feedback amplifier ‘quantizes’

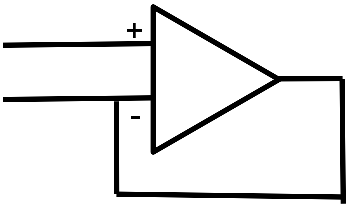


$$V = \mathrm{sat}_1(I + KV) \quad \equiv \quad V = \begin{cases} +1 & I \geq -1 - K \\ -1 & I \leq K - 1 \end{cases}$$

Sensitivity domain is spread by positive feedback

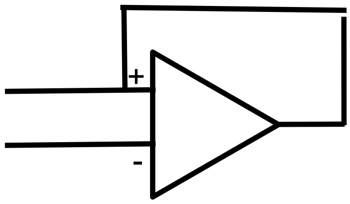
Hysteretic behavior: memory, ON-OFF devices
(The essence of digital technology)

The feedback amplifier principle



- Negative feedback linearizes
- Continuous behavior
- Analog technology
- exogenous

(output primarily reflects the input)

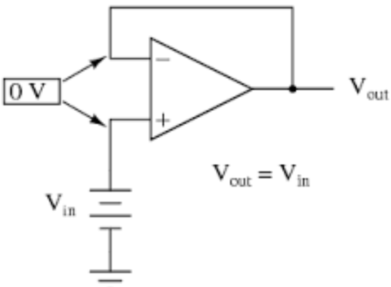


- Positive feedback quantizes
- On-Off behavior
- Digital technology
- endogenous

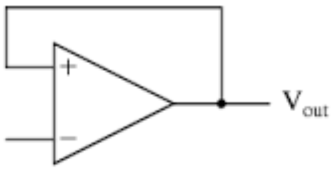
(output primarily reflects memory of the past)

The success of negative feedback turned positive feedback into history.

Negative feedback



Positive feedback



> Positive feedback, as something deliberately intended, is nowadays of much less significance than negative feedback, which forms the basis of control systems. In terms of mechanical systems, negative feedback in the form of governors was important long before positive feedback was recognized either implicitly or explicitly. But in electronic circuits it was the other way round; positive feedback for a couple of decades from 1912 reigned supreme, and negative feedback was something 'invented' for electronic systems around 1930.

(Tucker, 1972)

A historical hint : the rise of cybernetics

1920... 1927 1952

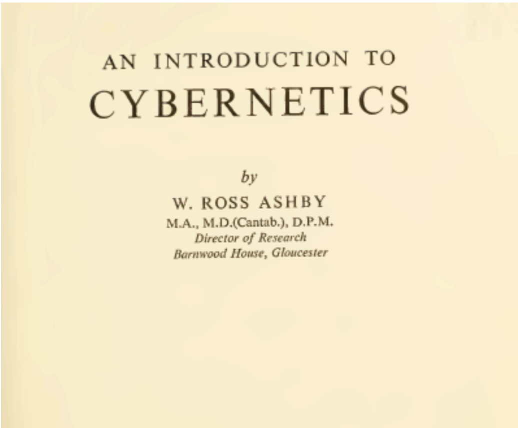
Ashby

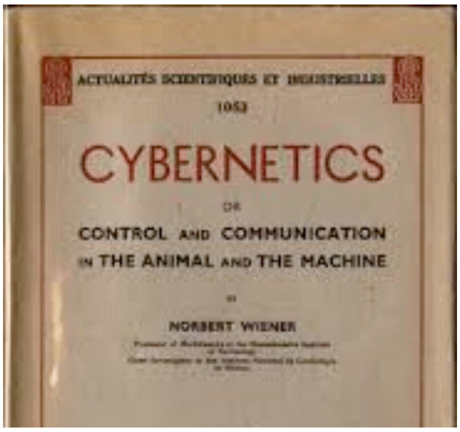
Black amplifier

Wiener

Hodgkin & Huxley

Turing





The digital age turned cybernetics into history

1952

The digital age

2015

Crick & Watson

Von Neumann

computer

internet

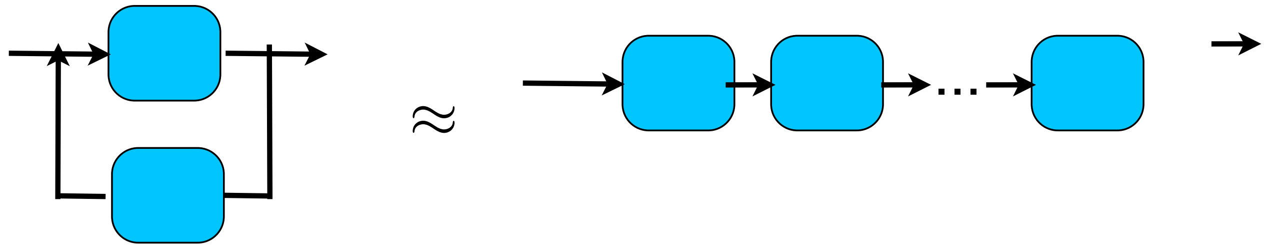
AAGTCAAGCTGCTCTGTGGGCTGTGATCTGCCTCAAACCCACAGCCTGGGTAGCAGG
AGGACCTTGATGCTCCTGGCACAGATGAGGAGAATCTCTCTTTTCTCCTGCTTGAAG
GACAGACATGACTTTGGATTTCCCCAGGAGGAGTTTGGCAACCAGTTCCAAAAGGCT
GAAACCATCCCTGTCCTCCATGAGATGATCCAGCAGATCTTCAATCTCTTCAGCACA
AAGGACTCATCTGCTGCTTGGGATGAGACCCTCCTAGACAAATTCTACACTGAACTC
TACCAGCAGCTGAATGACCTGGAAGCCTGTGTGATACAGGGGGTGGGGGTGACAGAG
ACTCCCCTGATGAAGGAGGACTCCATTCTGGCTGTGAGGAAATACTTCCAAAGAATC
ACTCTCTATCTGAAAGAGAAGAAATACAGCCCTTGTGCCTGGGAGGTTGTCAGAGCA
GAAATCATGAGATCTTTTTCTTTGTCAACAAACTTGCAAGAAAGTTTAAGAAGTAAG
GAATGA, TGTGATCTGCCTCAAACCCACAGCCTGGGTAGCAGGAGGACCTTGATGC
TCCTGGCACAGATGAGGAGAATCTCTCTTTTCTCCTGCTTGAAGGACAGACATGACT

A methodological hint

There is no theory of feedback in the digital age

Recurrence is usually associated to intractability.

We go around this limitation by substituting feedforward to feedback



Examples abound in information theory, signal processing, machine learning, graphical modeling, automata theory.

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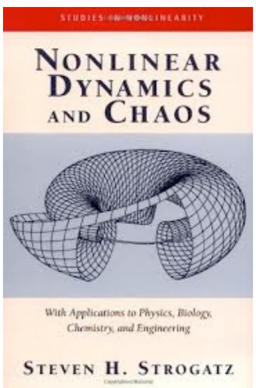
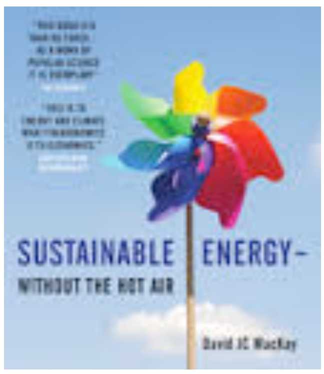
Feedback : the great absent of mathematical science

Occurrences of the word "feedback" are exceptional throughout physics, mathematics, and computer science. Usually associated to "positive feedback" (autocatalysis, ...)

revealing statistics:



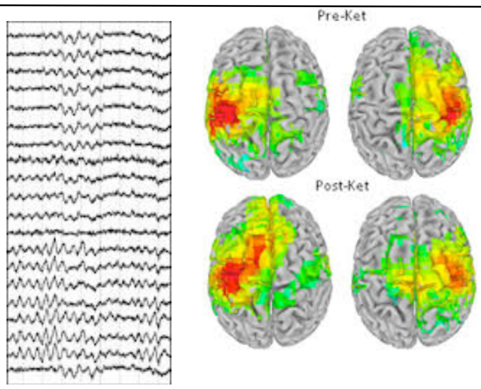
3 occurrences
(positive feedback)



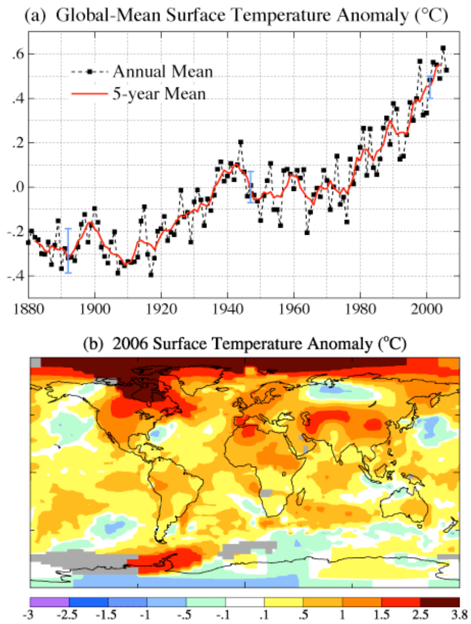
3 occurrences
(positive feedback)

An architecture for multiresolution behaviors

individuals / families / collectivities / countries / ...



.../cells/circuits/ brain areas/ whole brain



years / centuries / millenia
mm / cm / km / ...

Complexity, feedback, and sensitivity

Open and closed systems

The analysis tools of complex behaviours are inherited from questions raised by celestial mechanics.
Those questions are formulated in the language of closed systems.
Instead, current questions pertaining to complexity are about large interconnections of open systems.

Feedback

Feedback is central to study interconnections.
Feedback is essential to localisation. Localisation is essential to tractability.
Feedback is an essential bridge between analog and digital behaviours

Sensitivity

Complex systems are about interconnections between the tiny and the large.
Sensitivity analysis is a central analysis tool of control theory.

A common theme:
How to model the interconnection between the small and the large ?

Lecture 1 : the local and the global. A control theorist viewpoint

Lecture 2 : the complexity of sensitivity analysis across scales

Lecture 3 : a simple paradigm for robust control across scales