

Practical Investigations of Complex Systems

Defence Presentation of
a Thesis
in the Department of
Computer Science and Software Engineering

Presented in partial fulfilment of the requirements
for the degree of Doctor of Philosophy

Concordia University
Montréal, Québec, Canada

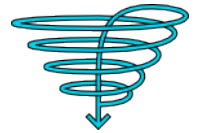
Nicolas Brodu, June 2007

Outline

Introduction.....Emergence and Complexity



Downward Causation.....Global control



Edge of Chaos.....Between order and randomness



Algorithms.....Tools and techniques



Conclusion.....Theoretical and practical





Emergence

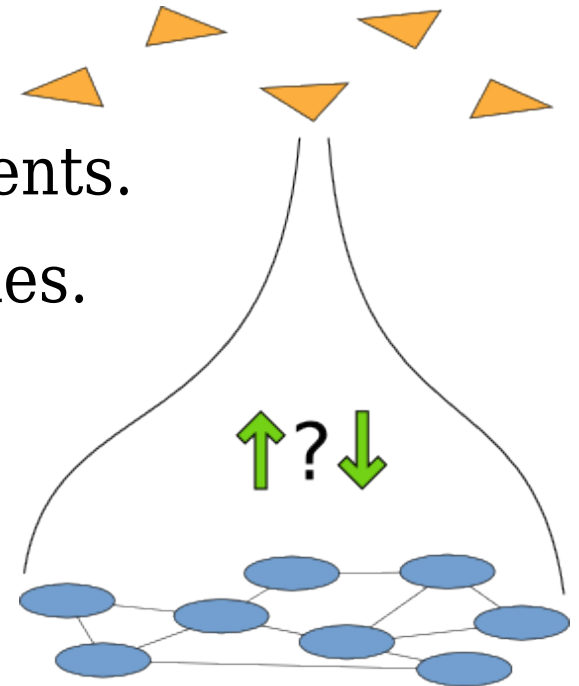
Introduction
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Levels of investigation

- Interactions between micro-scale elements.
- Functionally defined higher-scale entities.
- Micro-macro relationships?

Reductionism & Holism

- Low-level formal system is not enough.
- But... Understanding implies building relations.
- Soon another formal system, to which we “reduce” to.
- Supervenience reconnects formal systems.



Emergence is usually when “reductionism” fails



Dealing with Complexity

Introduction
2 / 2

The experimental scientific method!

- Formulate testable hypothesis, formal systems if possible.
- Build models accordingly, make predictions.
- Validate or refute the models, refine theory, and loop.

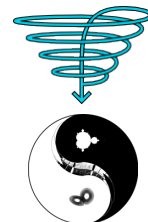
⇒ New science not needed, applying the current one is

- Create new tools & techniques when necessary.
- Use the computer as an exploratory instrument.



My choice for this thesis: two controversial issues

- Downward causation.
- Edge of Chaos hypothesis.





Downward Causation

Downward
Causation
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Causation links:

- Upward Micro \Rightarrow Macro is usually assumed.
- Downward is controversial: How? Extent of causality?

Solution:

- Avoid semantic closure trap (word graph vs. meaning).
- Do not mix entities with \neq definitions (formal/functional).

A practical example: Global control

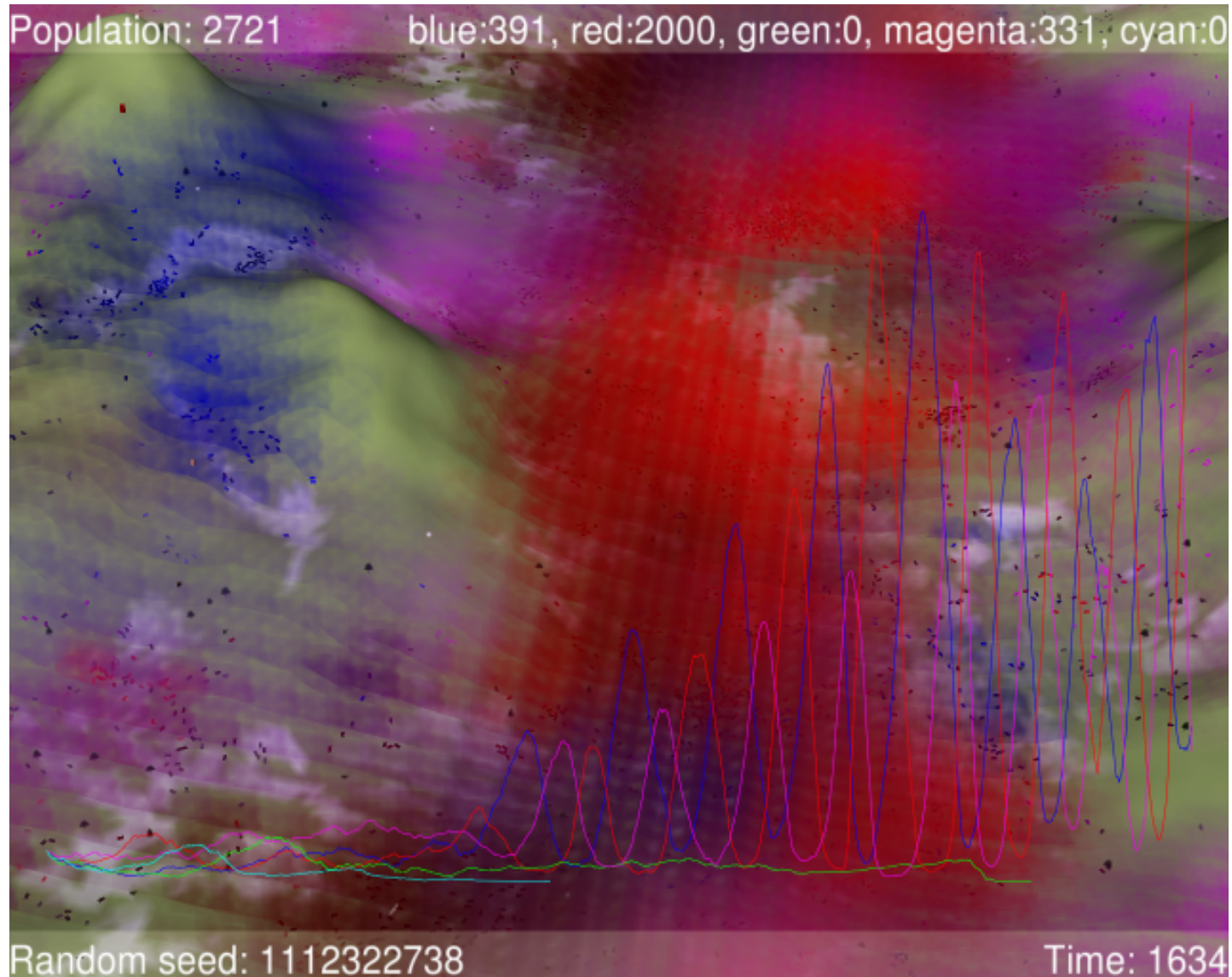
- Involve high-level notions not defined at the low level.
- Micro states changed by using high-level notions.

Experiment performed in an Artificial Life system



Artificial Life experiment

Downward
Causation
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Top-down control

Downward
Causation
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Artificial life system

- Global notions G like population cycles.
- Low-level parameters L , mainly linked to energy.
- Open & dissipative system, equilibrium if any is dynamic.

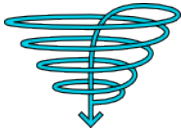
Micro \rightarrow Macro empirical map

- Batch: below, at, above each parameter.
- Average each batch to build gradient map.
- Ideally probability distributions $p(G|L)$.

	L_1	L_2	L_3
G_1	\nearrow	\nearrow	\cap
G_2	\searrow	\downarrow	\nearrow
G_3	\cup	\nearrow	\nearrow
G_4	\searrow	\downarrow	\approx
G_5	\uparrow	\cap	\approx

Macro \rightarrow Micro driving the system

- Express higher-level objective, then gradient “descent”.



Results

Downward
Causation
4 / 4

Chosen goal: Toward a stable and rich ecosystem

- No final world domination of a species.
- More population cycles.
- Less or no species extinctions.

By using local parameters

- grass density.
- mass limits.
- life costs.

Follow gradient

- Control OK.

	max. mass	min. mass	mass/energy conv.	max. energy	spore threshold	spore cost	self-maintenance	grass density	grass growth rate	gradient descent	Desired goal
Time to domination	↗	↘	↘	↘	↘	↘	↘	↘	↘	↗	↗
Population cycles	≈	≈	↑	↘	↘	↘	↘	↑	↑	↗	↗
Extinction count	↘	↘	↘	↘	↘	↗	↗	↘	↘	≈	↘
Hunters / Grazers ratio	↗	↘	↗	↘	↘	↘	↘	↘	↗	↗	↗
Time to extinction	↘	↗	↘	↘	↘	↗	↘	↗	↘	↘	↗
Spawning frequency	↘	↘	↗	↘	↘	↘	↘	↗	↗	↗	↗
Life time span	≈	≈	↘	↗	≈	↗	↘	↘	↘	↘	
Life time / species time	↗	≈	↗	↗	↗	≈	≈	↘	↗	↘	
<i>Actions</i>	+	+	-	-	-	-	=	+	-		



Edge of Chaos

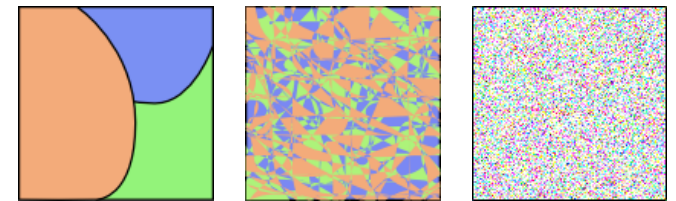
Edge of Chaos
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Hypothesis: Critical region between order and chaos

- Order: Information destroyed, no advanced features.
- Chaos: States statistically not distinguishable, “random”.
- In between: Best properties, long transients, complexity.

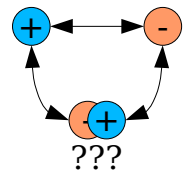
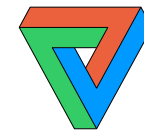
But:

- What properties to measure?
- How to assert order/chaos states?



Solution: design experiment explicitly

- Use order & chaos considerations to direct a system.
- Monitor system states, should identify a critical region.



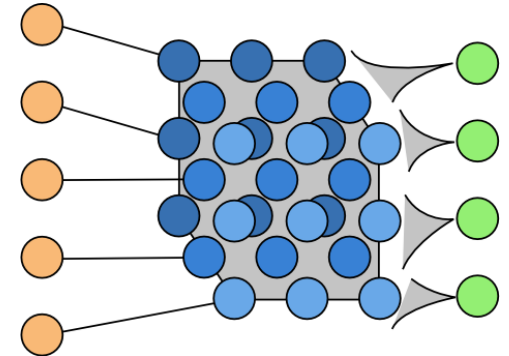


Spiking Neurons

Edge of Chaos
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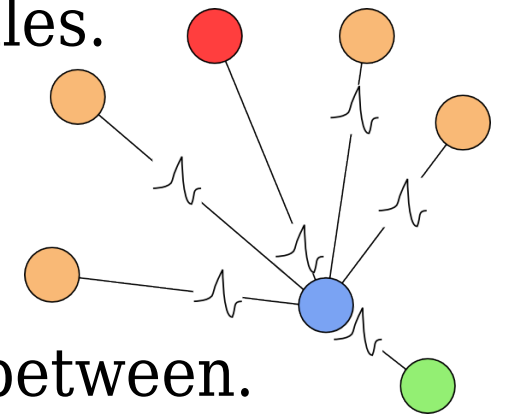
Liquid State Machines

- Reservoir computing adapted to the task.
- Hebbian learning, result easy to monitor.



System performance and order/chaos considerations

- Propose a whole family of new learning rules.
- Only interpretable using Edge of Chaos.



Monitoring the system state

- Indicators low for order & chaos, high in between.
- Separation: Ability to distinguish I/O mappings.
- Statistical complexity: Quantify prediction difficulty.



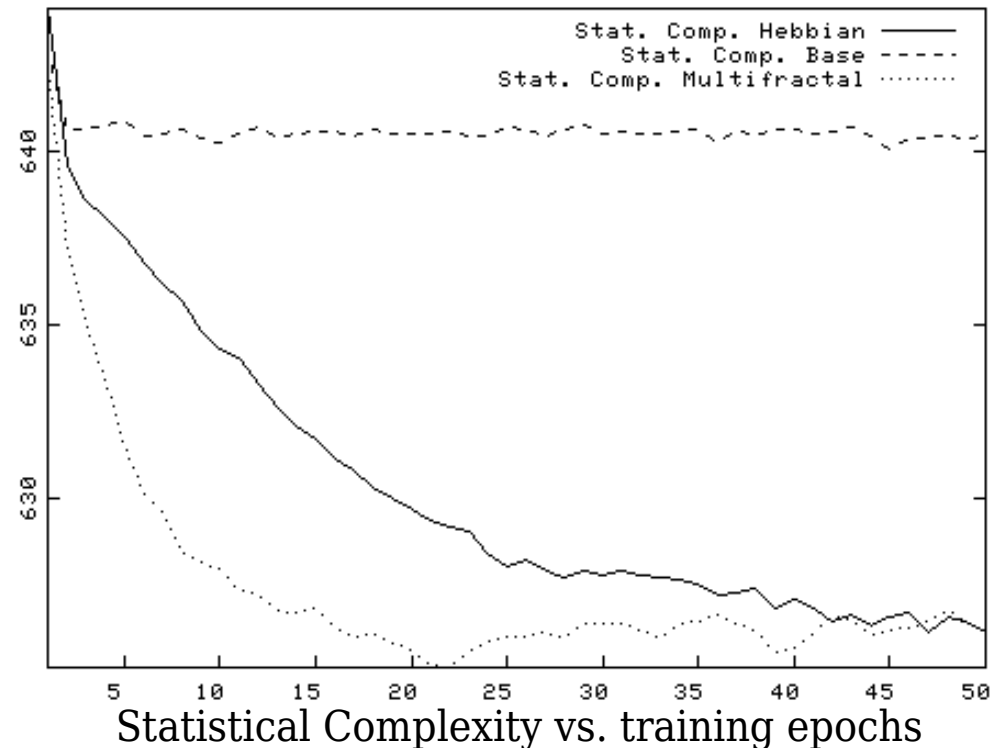
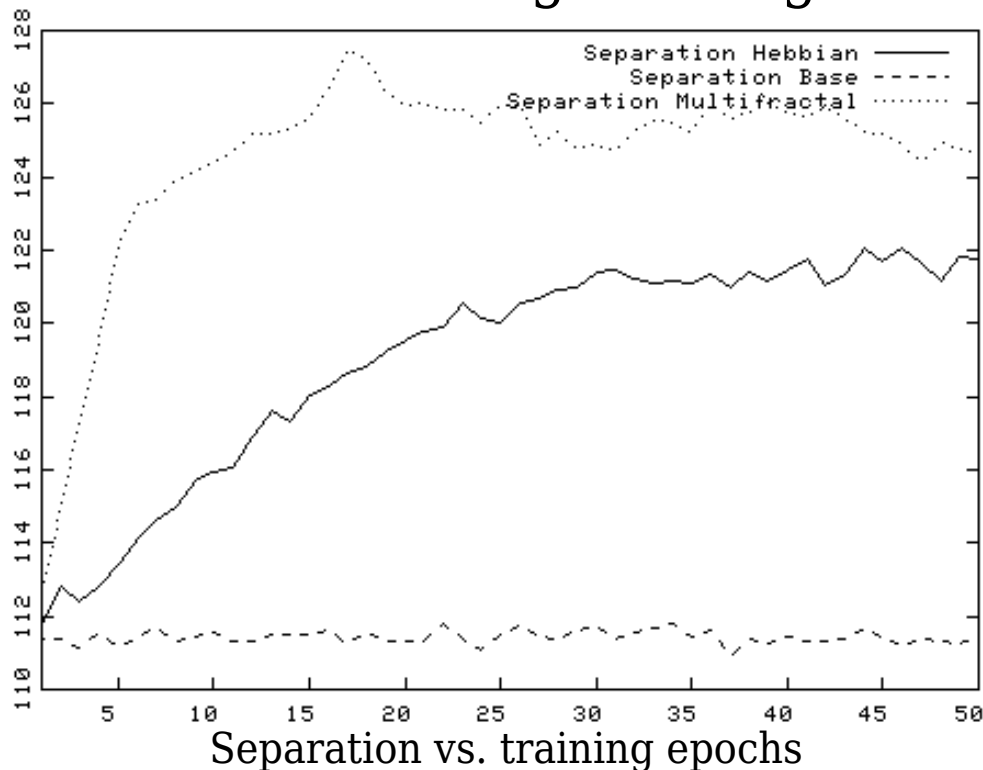
Results

Edge of Chaos
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Testing classification error on a real data set:

	No training	Hebbian	Multifractal
Test classification error mean	6.20%	5.70%	5.73%
Test classification error dev.	1.71%	1.34%	1.58%

Indicators during training on the reduced data set:





Interpretation

Edge of Chaos
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New learning rule validated

- Works as intended, similar to existing rule.
- Edge of Chaos supported by this particular result.

Unexpected information from the indicators

- One increases (separation), the other decreases.
- No system state shift toward a unique critical region.
- Edge of Chaos globally refuted on the system!

New interpretation

- Each indicator may peak at a distinct “critical” region.
- No global Edge of Chaos for the whole system!



Incremental Complexity

Algorithms
1 / 3

One of the necessary tools & techniques developed.

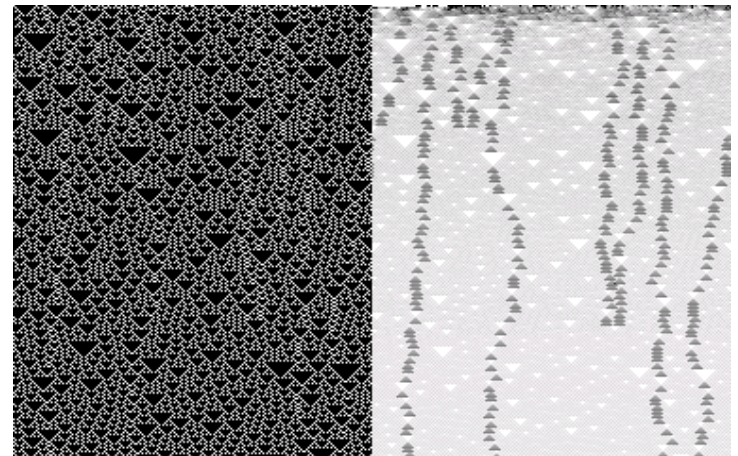
- Previous algorithm not adapted to a system that changes.
- Efficiency considerations.

Needs: Incremental implementation

- Can remove expired data, add new values.
- Up-to-date estimate maintained, non-stationary systems.

Validated on Cellular Automata

- Similar results as Shalizi *et al.*
- Fast convergence.
- Local pattern detection.





Incremental Multifractal

Algorithms
2 / 3

Multifractal Analysis

- Irregularities & self-similarity of a time series.
- Condensed information, was ideal for new learning rule.
- But needed to be incremental.

Wavelet decomposition method

- Time-frequency decomposition, reconstruct at \neq scales.
- Then get multifractal spectrum by fitting exponentials.

Incremental algorithm

$X_{0 \rightarrow 5}$		$X_{2 \rightarrow 7}$		$X_{4 \rightarrow 9}$		$X_{6 \rightarrow 11}$		$X_{8 \rightarrow 13}$		$X_{10 \rightarrow 15}$						
X_0	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}
$X_{1 \rightarrow 6}$		$X_{3 \rightarrow 8}$		$X_{5 \rightarrow 10}$		$X_{7 \rightarrow 12}$		$X_{9 \rightarrow 14}$		$X_{11 \rightarrow 16}$						

- Sharing wavelet decomposition over \neq frames.
- Intermediary fitting results shared with wavelet data.

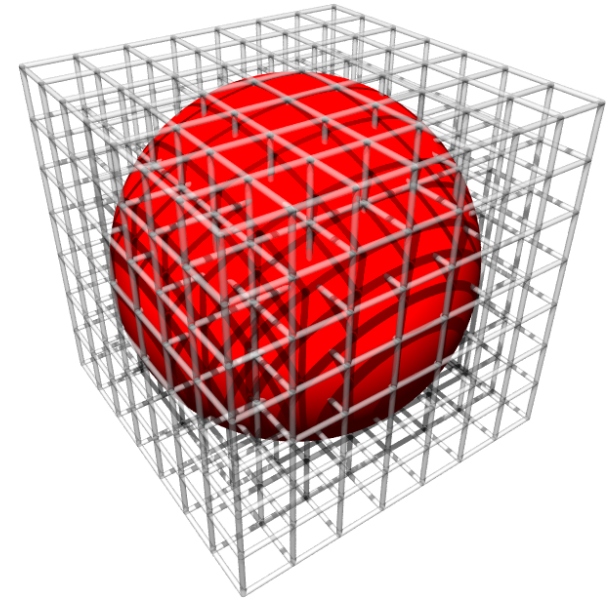


Neighbourhood Queries

Algorithms
3 / 3

Problem found in many domains

- Finding the nearest neighbours.
- Trees not adapted to moving objects.
- Ex: AI routine in artificial life system.



Original Solution

- Indexing the query sphere (centre, maximum distance).
- Running through the list of cells making up the sphere.
- Premature stopping possible for K -nearest neighbours.
- Wrapping worlds taken into account.

Appreciable gains up to 60% in some benchmarks

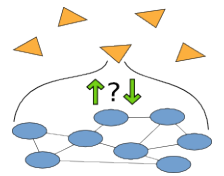


Theoretical Advances

Conclusion
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Point of view on reductionism in simulations

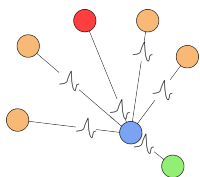
- Simulations OK even for formally irreducible emergence.
 - Cannot distinguish from incompressible one anyway.
- Reductionism & Holism: compatible & necessary.
 - Understandable functionalism \Rightarrow higher-level formal system.
 - Reconnect with lower-level using supervenience.



Refinements of the Edge of Chaos hypothesis



- Order and chaos considerations are useful.
 - Used predictively \rightarrow family of learning rules, one that works.
 - \Rightarrow Insight on previous rule & quantified neuron specialisation.
- Edge of chaos is globally invalid, OK w.r.t. an indicator.





Practical advances

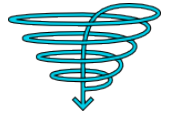
Conclusion
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New generically applicable algorithms



- Incremental statistical complexity.
- Incremental multifractal analysis.
- More efficient dynamic neighbourhood queries.

A usable form of downward causation & control



- Top-down control is possible.

But more importantly:

- New science not necessary, current method applicable.
- Advocate use of computer as an experimental tool.

Thanks for your attention!

Web and publication information

Web page and source code: <http://nicolas.brodu.free.fr>

E-mail address: nicolas.brodu@free.fr

Publications:

Quantifying the effect of learning on recurrent spiking neurons, April 2007,
Nicolas Brodu. To appear in the IJCNN07 conference.

Learning using Dynamical Regime Identification and Synchronization, April 2006,
Nicolas Brodu. IEEE World Congress on Computational Intelligence, IJCNN06
proceedings pp662-668.

Environmental fitness for sustained population dynamics, September 2005,
Nicolas Brodu. IEEE Congress on Evolutionary Computation CEC05, Vol 1,
pp343-350.

Accepted with changes, new version resubmitted:

Query Sphere Indexing for Neighborhood Requests, June 2007, Nicolas Brodu.
Conditionally accepted to the Journal of Graphics Tools.

Submitted, no answer yet:

Real-time update of multi-fractal analysis on dynamic time series using
incremental discrete wavelet transforms, November 2005, Nicolas Brodu.