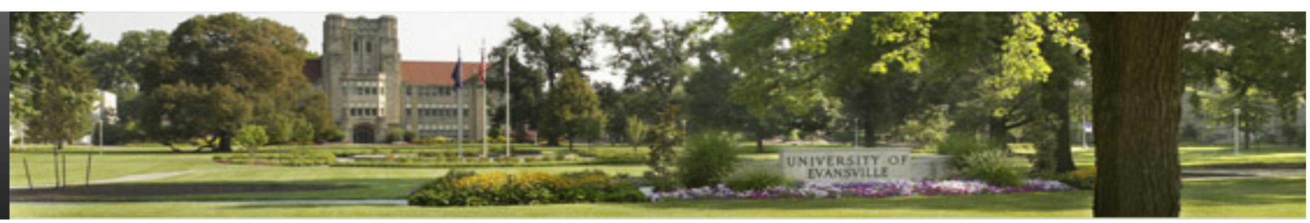
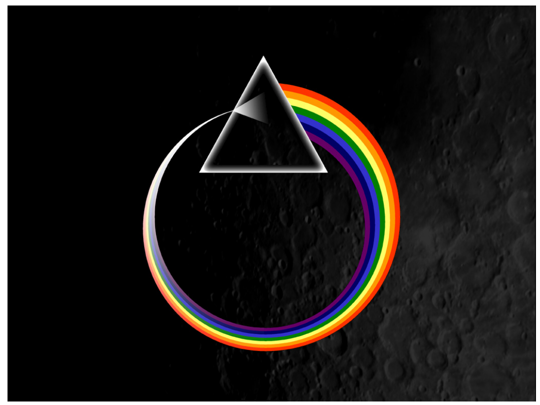
Info-Metrics Institute Workshop: Philosophy of Information
American University, Washington D.C.
October 3rd, 2011

A Brief Introduction to
Information-Theoretic Teleodynamics

Based on A. Beavers & C Harrison. (2012). Information-Theoretic Teleodynamics in Natural and Artificial Systems. Forthcoming in *A Computable Universe: Understanding Computation and Exploring Nature as Computation, H. Zenil, (Ed). World Scientific.*

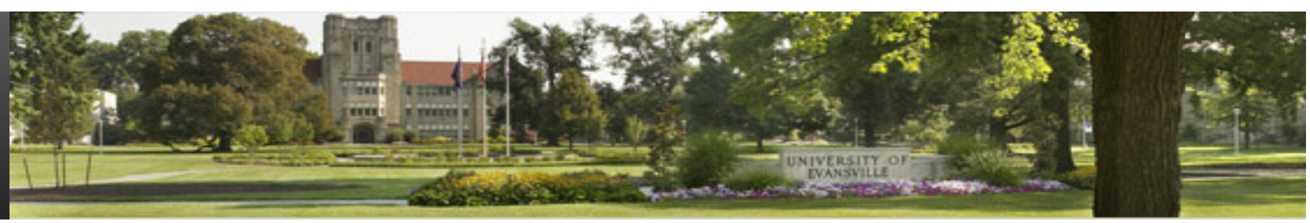


A Brief Introduction to Information-Theoretic Teleodynamics (ITT)

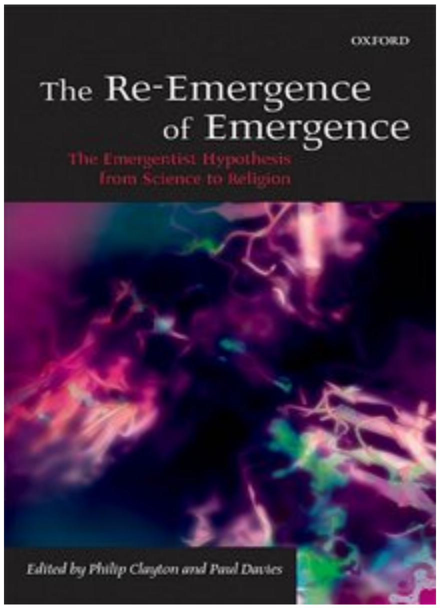


"Circularity is … the key to unlocking the mystery of the apparent time-reversed causality of self-organizing and teleological processes."

T. Deacon (2006). Emergence: The Hole at the Wheel's Hub. In *The Re-Emergence of Emergence: The Emergentist Hypothesis from Science to Religion*, P. Clayton and P. Davies (Eds.). Oxford, UK: Oxford.



Thermodynamics, Morphodynamics and Teleodynamics



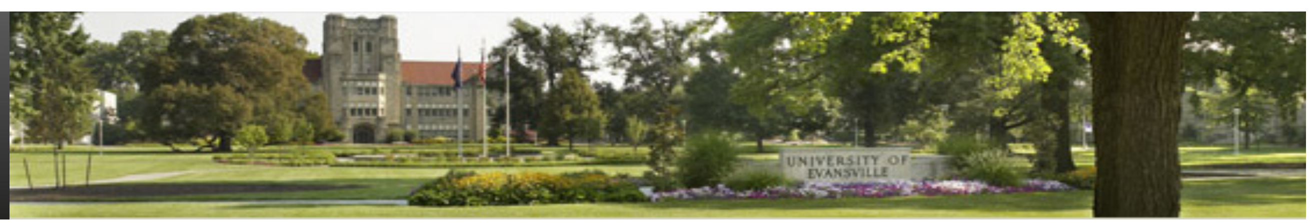
Terrence W. Deacon, "Emergence: The Hole at the Wheel's Hub," 111-150.

- Thermodynamics *(first order emergence)*
- Morphodynamics *(second order emergence)*
- Teleodynamics *(third order emergence)*

These are NOT mere philosophical distinctions!

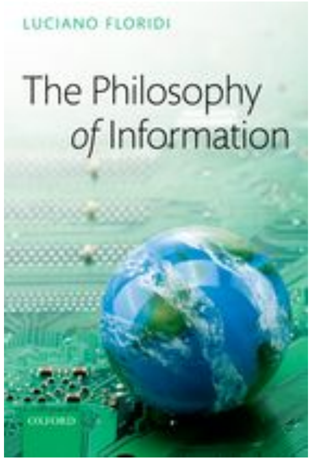
Deacon is an anthropologist at Berkeley with specializations in biological anthropology and neuroscience.

Edited by Philip Clayton & Paul Davies, Oxford 2006.



Our Definition of ITT (Not Deacon's)

"Information-Theoretic Teleodynamics is an approach to intelligence in both natural and artificial systems that uses the quantity and distribution of information to drive goal-oriented behavior without recourse to semantic content." (Beavers and Harrison, forthcoming)



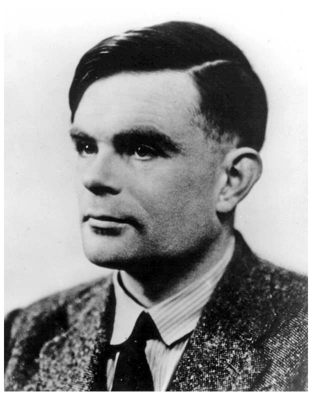
Oxford 2011

Answers to one of Floridi's *Open Problems in the Philosophy of Information*:

"Do information or algorithmic theories … provide the necessary conditions for any theory of semantic information?" (p. 31).

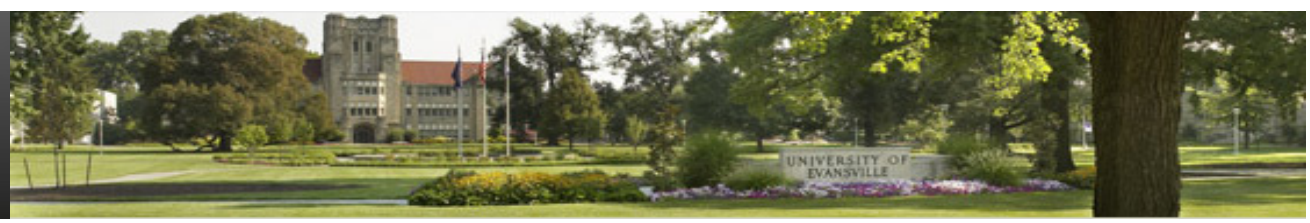
Our Hypothesis

It is possible to reduce semantic information to the quantification of information flow *provided that other conditions respecting the internal structure of an agent and its relations to its environment are met*.



"It is … quite difficult to think about the code entirely in abstracto without any kind of circuit."

- Alan Turing 1947

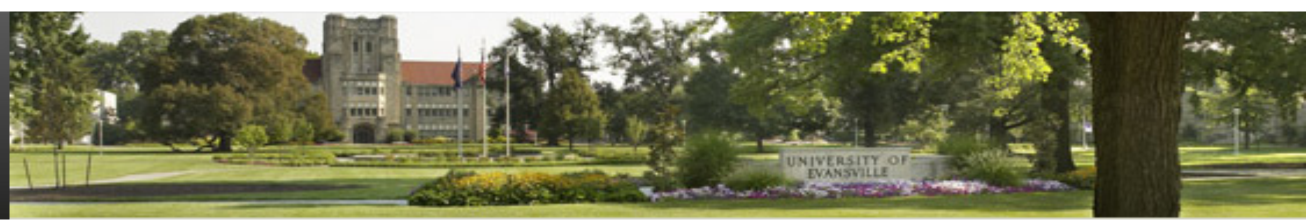


Our Method

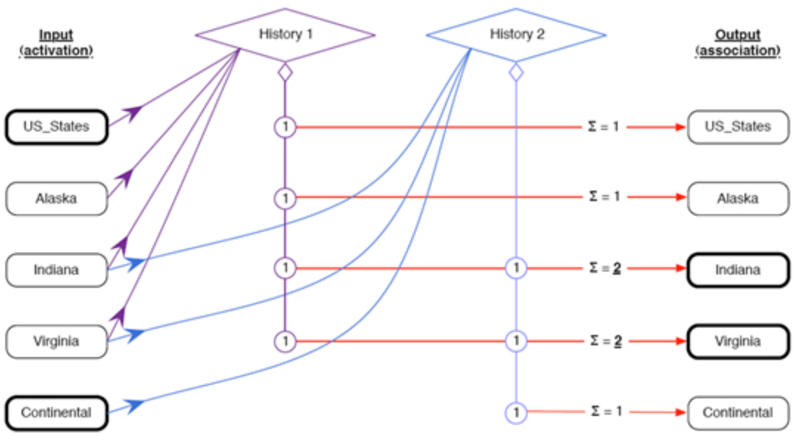
Computational Philosophy: The use of computational techniques to aid in the discovery of philosophical insights that might not be easily discovered otherwise.

Philosophical (Cognitive) Modeling: The use of computer models to illuminate epistemic and informational processes that govern behavior and decision making while helping to settle some philosophical questions and raise others.

In other words, philosophical modeling hopes to resituate the interrogative terrain of philosophy so that headway can be made on pressing issues of current philosophical concern.

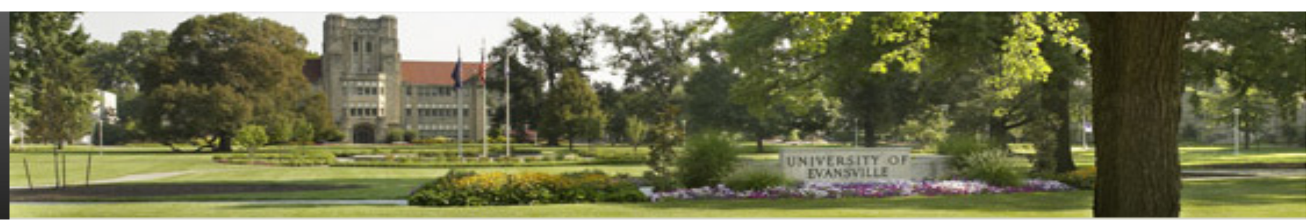


Dynamic Associative Networks: Circuits Not Software

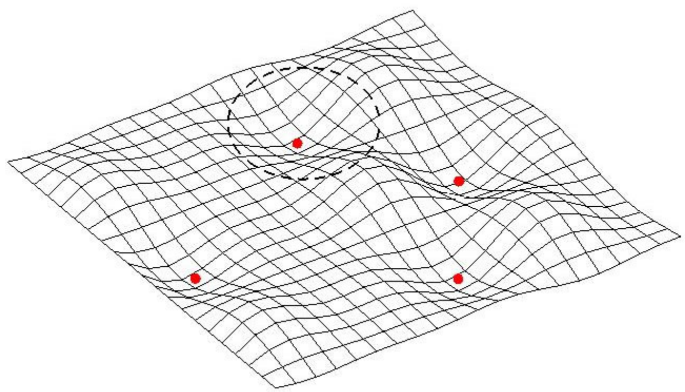


- DANs vs ANNs
- Hebbian Learning with Circuits

1. Object identification with context sensitivity
2. Comparison of similarity and difference
3. Automatic document classification
4. Shape recognition on a grid
5. Association across simulated sense modalities
6. Primary sequential memory
7. Network branching across subnets
8. Eight-bit register control
9. Rudimentary natural S&R language processing



Information Entropy and Teleodynamics



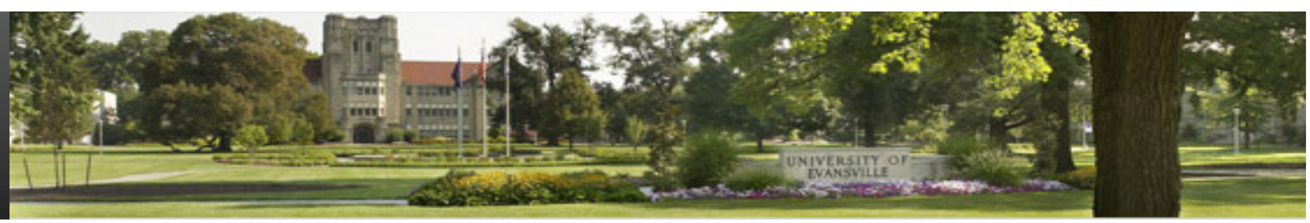
Hopfield Attractor from Scholarpedia

Shannon Information Entropy (1948)

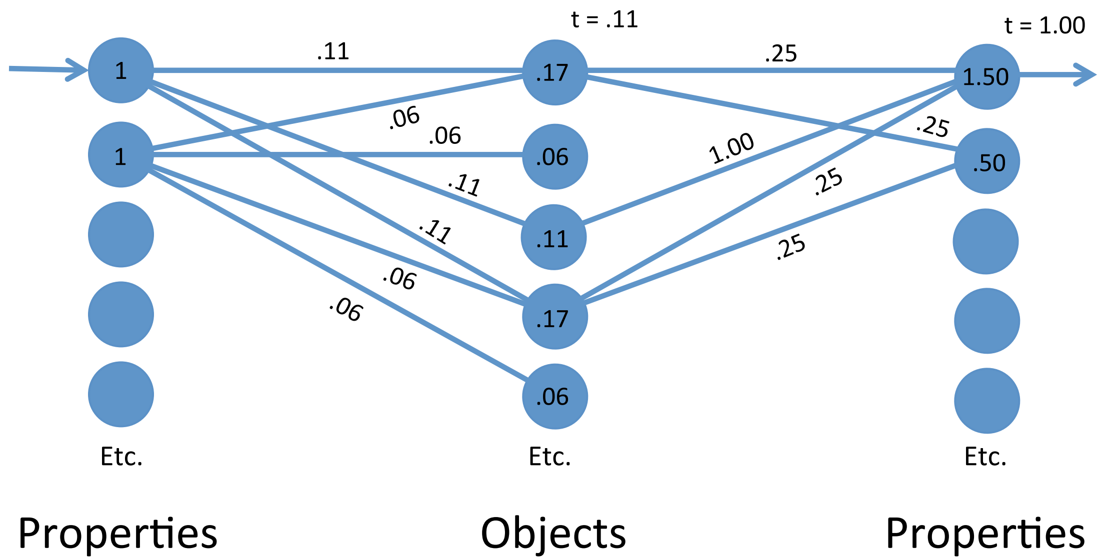
The more random a piece of information the more it may decrease our ignorance.

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log_b p(x_i)$$

Hence, on a semantic reading, as entropy rises so does the informativeness of a piece of information. In what follows, we use the concept and not the formula for information entropy.

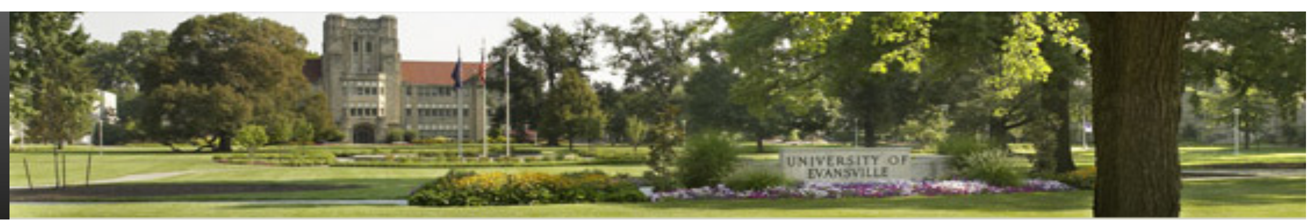


Sample DAN Recurrent Wiring Schematic



Property Set: small, furry, meows, barks, winged, flies, swims, finned, crawls, many-legged (more than four), two-legged, warm-blooded, live off- spring, walks, four-legged, farm animal, oinks, moos, ridable, big, crows, woodland, hops, hoofed, curly, hisses, cold-blooded, scaled, quacks, coos, seafaring, spawns, large-mouthed, web-making, whiskered and feathered.

Object Set: dog, cat, bird, duck, fish, caterpillar, human, pig, cow, horse, rooster, rabbit, deer, retriever, poodle, mouse, snake, crocodile, lizard, turtle, dolphin, whale, ostrich, pigeon, shark, salmon, bass, house fly, cricket, spider, catfish and seal.

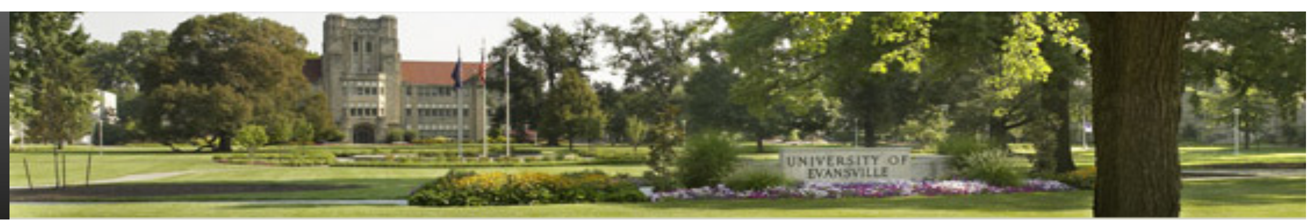


Sample Results using $1/n^2$

Note that flies has yet to be pulled into the list, since ostriches and roosters do not fly. However, on the next recursion, rooster and ostrich are slightly demoted (but only slightly), letting the generic bird with the duck and pigeon count for more (*and allowing the human, house fly and cricket to pass the threshold at a very low level*).

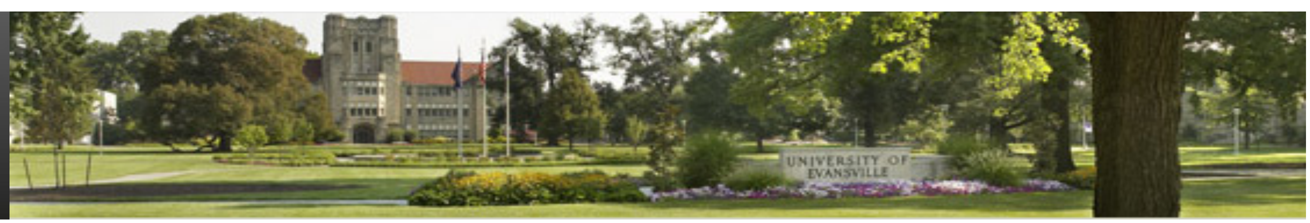
Typicality wins out on the recursion cycle over uniqueness, as flies is elevated over the threshold, further demoting the rooster and the ostrich. Many-legged, live offspring and cold-blooded are pulled into the property set, but they do not cross the threshold.

Further recursion after the third cycle produces no further re-evaluation of nodes, unlike in other networks that can take several hundred iterations to settle.



Open Questions

- What constitutes genuine teleological behavior? (Can we still accept Aristotle's definition that it is goal-oriented activity based on an agent's internal structure? If so, then we have it here in this model.)
- Is it possible to expand the model to include something more along the lines of planning before executing a plan of action?
- What should the entropy equations be for governing dynamic weight setting?
- How should we determine threshold values for deciding what information passes through the network?



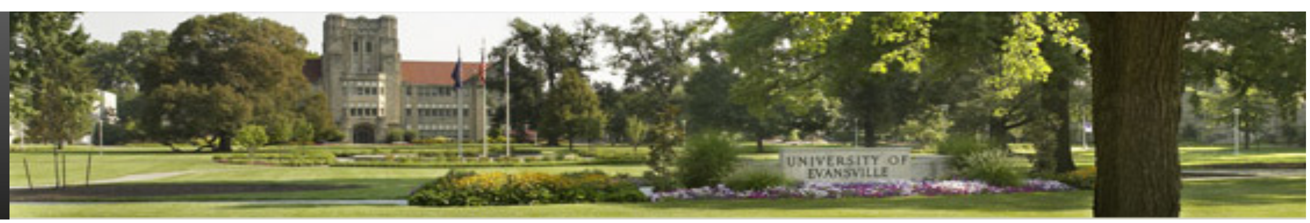
Past Work Related to this Presentation

Dynamic Associative Network Automatic Document Classification, **D. Burrows**, 2010-2011. Computer Science Senior Project for Noesis and the Indiana Philosophy Ontology Project. Funded by the National Endowment for the Humanities. *Winner of the 2011 University of Evansville Senior Project in Computer Science Award.*

Typicality Effects and Resilience in Evolving Dynamic Networks. In FS-10-03, AAAI Press, 2010.

Mechanists of the Revolution: The Case of Edison and Bell (with **B. Sigler**). In *Proceedings of the VIII European Conference on Computing and Philosophy*. Edited by Klaus Mainzer (Munich: Verlag Dr. Hut, 2010), 426-430.

More Fun with Jets and Sharks: Typicality Effects and the Search for the Perfect Attractors. North American Meeting of the International Association for Computing and Philosophy (IACAP), Simulations and Their Philosophical Implications, Carnegie Mellon University, July 24th-26th, 2010.



Past Work Related to this Presentation

Dynamic Associative Networks and Automatic Document Classification, **G. Wyant**, 2009-2010. Computer Science Senior Project for Noesis and the Indiana Philosophy Ontology Project. Funded by the National Endowment for the Humanities. *Winner of the 2010 University of Evansville Senior Project in Computer Science Award.*

Mechanical vs. Symbolic Computation: Two Contrasting Strategies for Information Processing. Society for Machines and Mentality, Eastern Division Meeting of the American Philosophical Association, New York City, December 27th-30th, 2009.

Modeling and Visualizing Dynamic Associative Networks: Towards Developing a More Robust and Biologically-Plausible Cognitive Model, **M. Zlatkovsky**. Computer Science/Cognitive Science Senior Project. *Winner of the 2009 University of Evansville Senior Project in Computer Science Award.* See companion website for details.

Phenomenology and Artificial Intelligence. In *CyberPhilosophy: The Intersection of Philosophy and Computing*, edited by James H. Moor and Terrell Ward Bynum (Oxford, UK: Blackwell, 2002), 66-77. Also in *Metaphilosophy* 33.1/2 (2002): 70-82.

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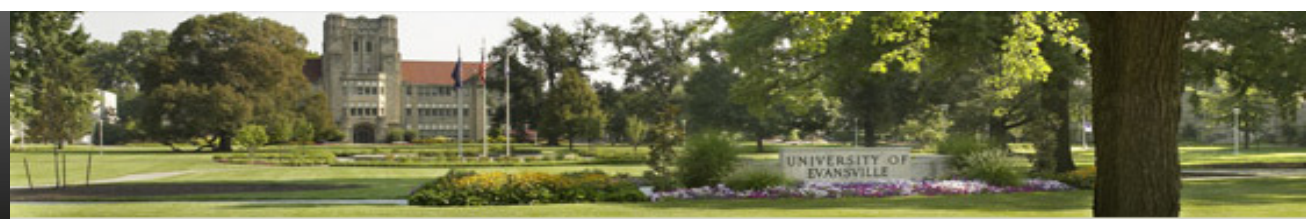

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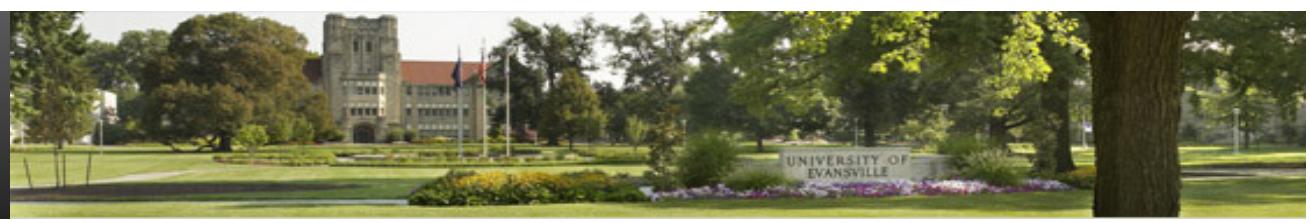
Appendices

UNIVERSITY OF EVANSVILLE
EST 1854 Civic Mission…Sacred Trust



Matthias Scheutz's Equivalency Proof

Note that the $index_i$ always refers to node i, and $maxact$ refers to the maximum activation a node can have as well as the default activation an input node gets.

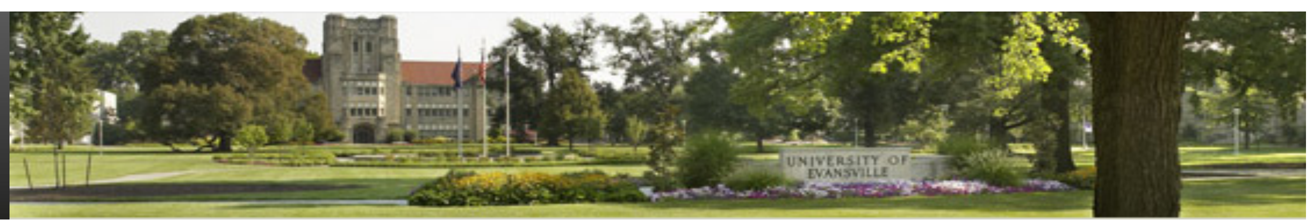
$$input_i(t) = f(t) = \begin{cases} maxact, & \text{if input applied at time } t \\ act_i(t-1) - 1, & \text{if } act_i(t) > 0 \\ 0, & \text{otherwise} \end{cases}$$

$$netin_i(t) = \sum_{i<-j} input_j(t)$$

$$act_i(t) = \begin{cases} net_i(t), & net_i(t) < maxact \\ maxact, & otherwise \end{cases}$$

We can now combine these into the following, where $extin_i(t) = 0$ if no input is applied, $maxact$ otherwise:

$$act_i(t) = f\left(\sum f\big(act_j(t-1) - 1 + extin_j(t)\big)\right)$$



Matthias Scheutz's Equivalency Proof

So, if the above captures the update equations of the network, then the additional application of f is not necessary. This is because:

$$f(f(a)+f(b)) = f(a+b) \qquad \text{for } a,b > 0$$

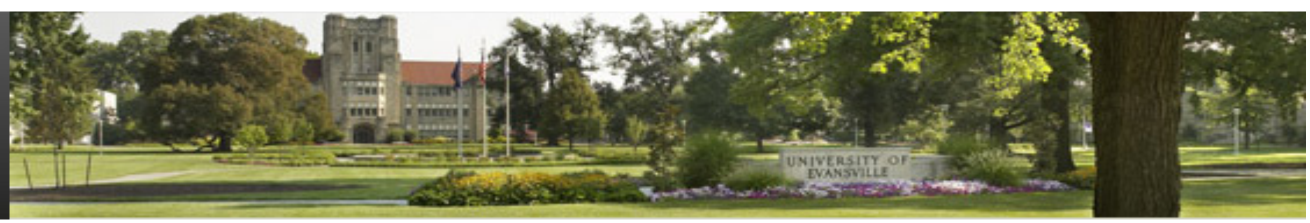
Proof: Suppose $a, b < maxact$, then $f(a) = a$ and $f(b) = b$ by the definition of f, and thus:

$$f(f(a) + f(b)) = f(a + b)$$

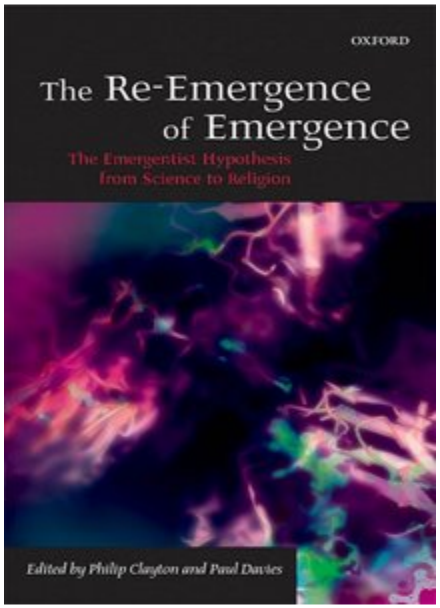
Now suppose that one of a or b $>= maxact$, let's say a. Then $f(a) = maxact$, again by the definition of f, and thus:

$$f(f(a) + f(b)) = f(maxact + f(b)) = maxact = f(maxact + b) = f(a + b)$$

Here we use twice the fact that $f(maxact + x) = maxact$ for $x > 0$.



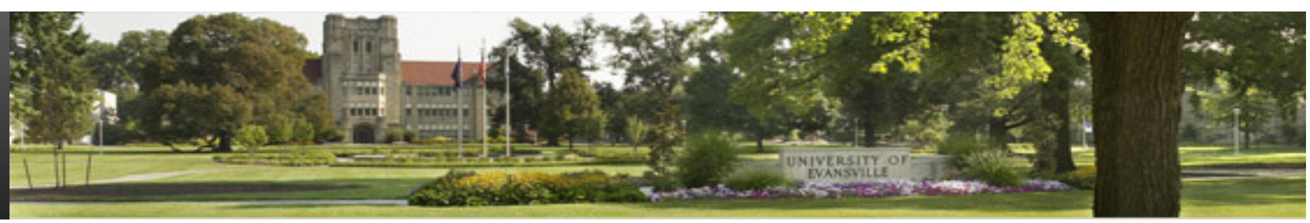
Deacon’s Thermodynamic Systems



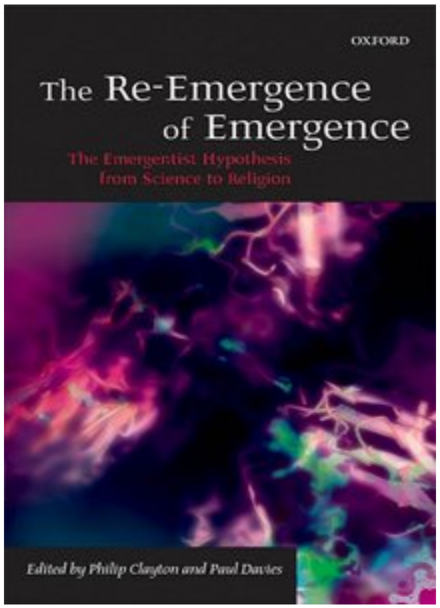
Thermodynamics *(first order emergence)*

- No top-down effects
- Fully reductive – can be fully explained solely in reference to parts
- Causally transparent
- Still admits of property asymmetry between parts and wholes
- Example: Liquidity

T. Deacon, “Emergence: The Hole at the Wheel’s Hub.”



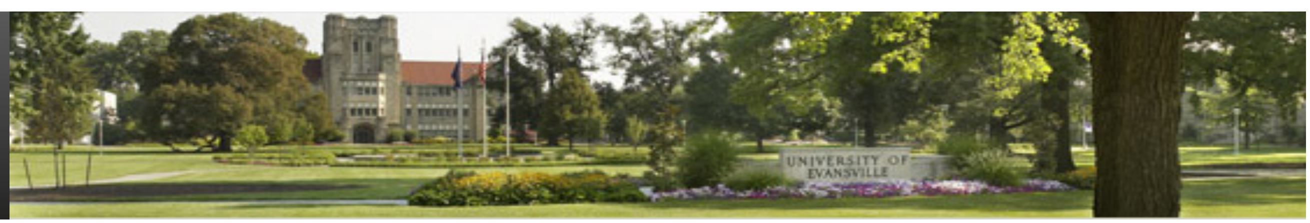
Deacon's Morphodynamic Systems



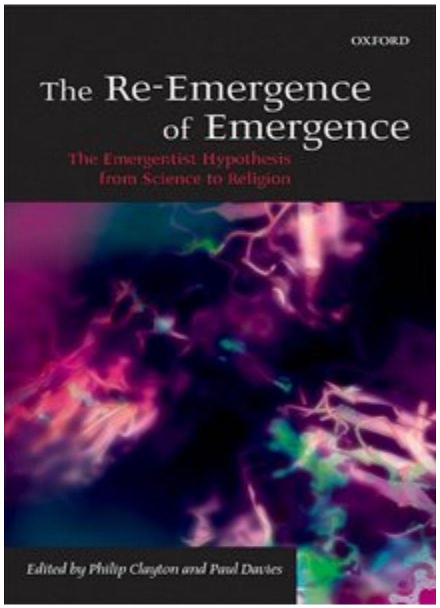
Morphodynamics *(second order emergence)*

- Emerges from thermodynamic systems
- Exhibits "simple recurrence" that enables self-organization
- Results from the instability of thermodynamic possibilities and environmental feedback that amplifies a stable pattern – past action restrains the space of future possibilities
- Examples: Bénard cells, snowflakes

T. Deacon, "Emergence: The Hole at the Wheel's Hub."



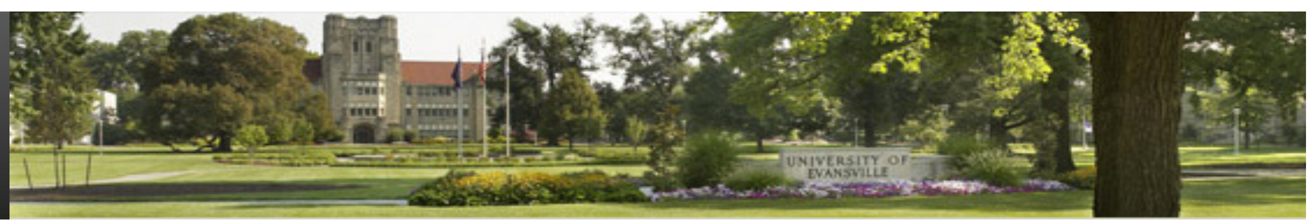
Deacon's Teleodynamic Systems



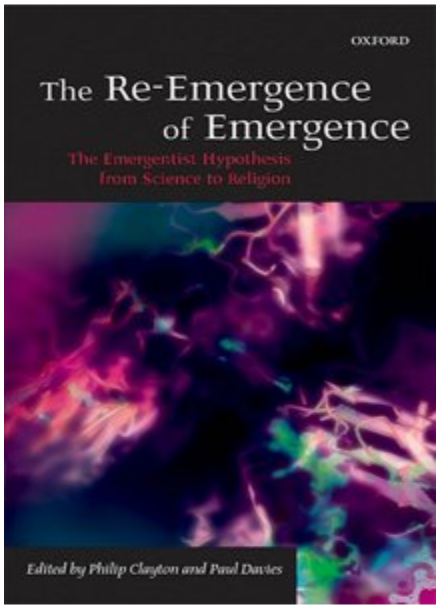
Teleodynamics *(third order emergence)*

- Emerges from morphodynamic systems
- Exhibits goal-oriented activity thanks to memory and information
- Results from the sampling of influences that select for "self-similarity maintenance"
- Uses a circular architecture of causal self-reference analogous to "attractors"
- Examples: Memory, evolution

T. Deacon, "Emergence: The Hole at the Wheel's Hub."



Deacon’s Teleodynamic Systems



Teleodynamics *(third order emergence)*

> “Third-order emergent dynamics are … intrinsically organized around specific absences. This physical disposition to develop toward some target state of order merely by persisting and replicating better than neighboring alternatives is what justifies calling this class of physical processes *teleodynamic*, even if it is not directly and literally a ‘pull’ from the future.” (143)

T. Deacon, “Emergence: The Hole at the Wheel’s Hub.”