Systems Concepts for the Simulation of Ultra-Large Networks

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DISTRIBUTED KNOWLEDGE SYSTEMS

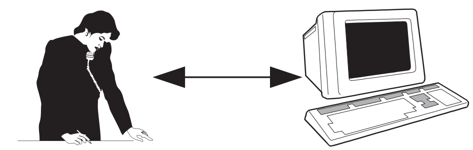
Distributed Knowledge Systems:

- Communities of interpreting agents
- Interacting with networked information resources
- Human-computer interaction at the *collective* level

LANL Needs:

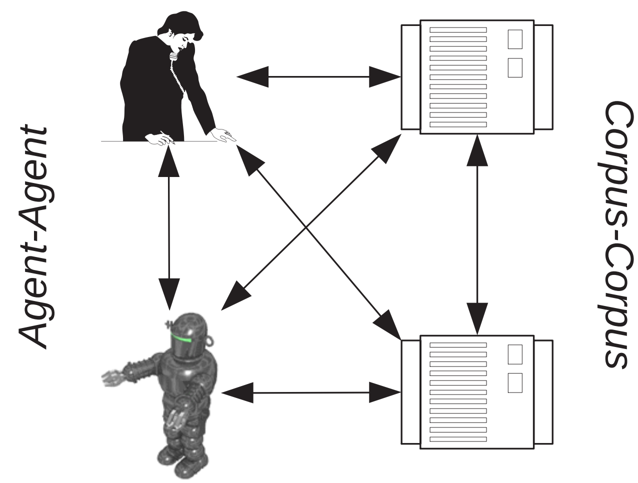
- Organization of massive corpora: weapons, bioinformatics, scientific publications and data
- Decision support for knowledge-based socio-technical organizations: infrastructure, command and control
- Meta-methodological collaborative scientific environments

Human-Computer



Traditional HCI

Agent-Corpus



DKS: **Collective** HCI

A SYSTEMS SCIENCE APPROACH

- Interdisciplinary modeling fields: foundation for "complex systems science"
- Bridge understanding across systems of different types by finding homomorphisms, isomorphisms
- Attempt to operationalize general concepts: *order, organization, information, structure, function, control*
- Especially **complexity** and **models**
- Emerging network-centric perspective:

  Cellular: Metabolic, genetic regulation

  Biological: Multi-cellular organisms, trophic

  Cognitive: Neural

  Socio-Technical: Social networks, knowledge networks, DKS, ULNs

ISSUES IN ULTRA LARGE NETWORKS (ULNS)

- Vast complexity: unprecedented levels of storage, computation, and connectivity
- Entrainment with real systems: infrastructure, markets
- Entrainment with communities of interpreting agents: implications for science, terrorism, *culture*
- Potential for emergent properties and behavior: novelty, unpredictability, unmodeled, *un-modelable?*
- *What mathematics, which models, what simulation methods, are appropriate?*

"CLASSICAL" PERSPECTIVE ON COMPLEXITY

- Weaver's Categories:

  Organized Simplicity: Crystal

  Unorganized Complexity: Gas

  Organized Complexity: All biological

- Search for operationalization of intuitive laws: "complexity increases with evolution"
- Search for quantitative measures:
  - Entropies: thermodynamic, statistical, dynamical
  - "Complexities": algorithmic, computational
  - Various other statistical "depths", "informations"

    JP Crutchfield and CR Shalizi, "Thermodynamic Depth of Causal States: Objective Complexity via Minimal Representations", *Physical Review E*, 59, 275-283, 1999

- Never satisfactory: *relative* and *user-dependent*
- Claimed to be failure

MODEL-BASED COMPLEXITY

- All knowledge is a model
- More than one model almost always *possible*: abstraction, scaling, meta-modeling
- Complexity is not of "the system", but of its model
- Complexity (R. Rosen): more than one model *necessary*
- Complexity (algorithmic): size of model approach size of system
- Hierarchical decomposition of models: general and *necessary* strategy to "handle complexity"
- *Identification* of hierarchical structure: not just from *design* (as in layered architectures) but also from *emergence* (as in evolved systems)

THE POINT

- Original question: *which class of formalisms, models, is appropriate?*
- Discrete dynamical systems approaches:
  - Graph theory
  - Collective automata
  - Robust modeling platforms
  - Identification of hierarchical structure, statistical simplifications
  - Limitations
- Beyond dynamical systems approaches:
  - Component systems
  - Agent systems
  - Semantic information

NETWORK ANALYSIS: SMALL WORLDS, RANDOM GRAPHS

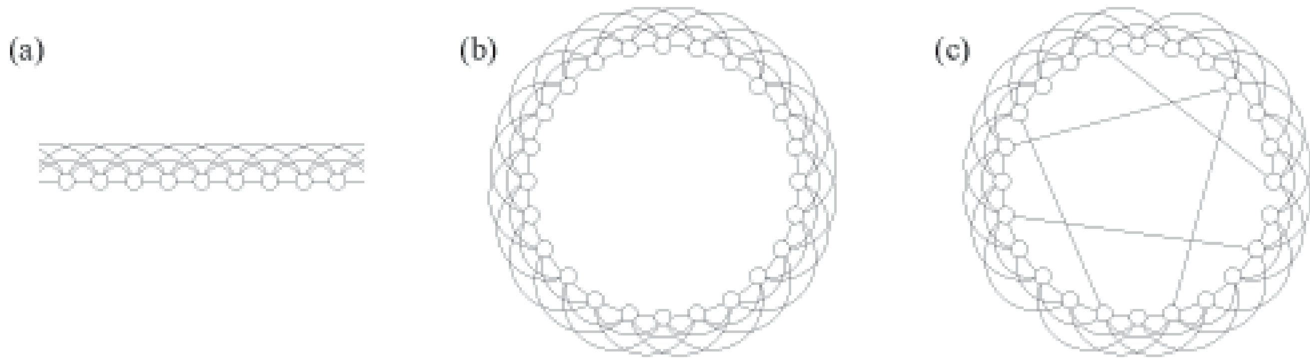


Figure 1: (a) A one-dimensional lattice with each site connected to its z nearest neighbors, where in this case z = 6. (b) The same lattice with periodic boundary conditions, so that the system becomes a ring. (c) The Watts–Strogatz model is created by rewiring a small fraction of the links (in this case five of them) to new sites chosen at random.

ME Newman, "Models of the Small World", *J. Stat. Phys.*, 101, 819-841, 2000

DS Callaway *et al.*, "Are Randomly Grown Graphs Really Random?", *Phys. Rev. E* 64, 041902, 2001

JM Kleinberg, "Navigation in a Small World", *Nature*, v. **406**, 2000

Thomas Stewart, "Six Degrees of Mohamed Atta", Business 2.0, `http://www.business2.com/articles/mag/print/0,1643,35253,FF.html`

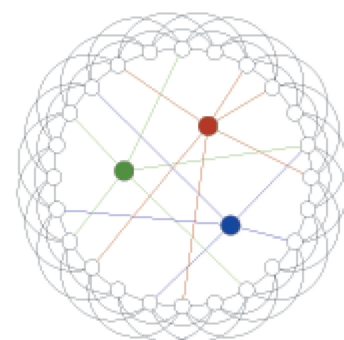
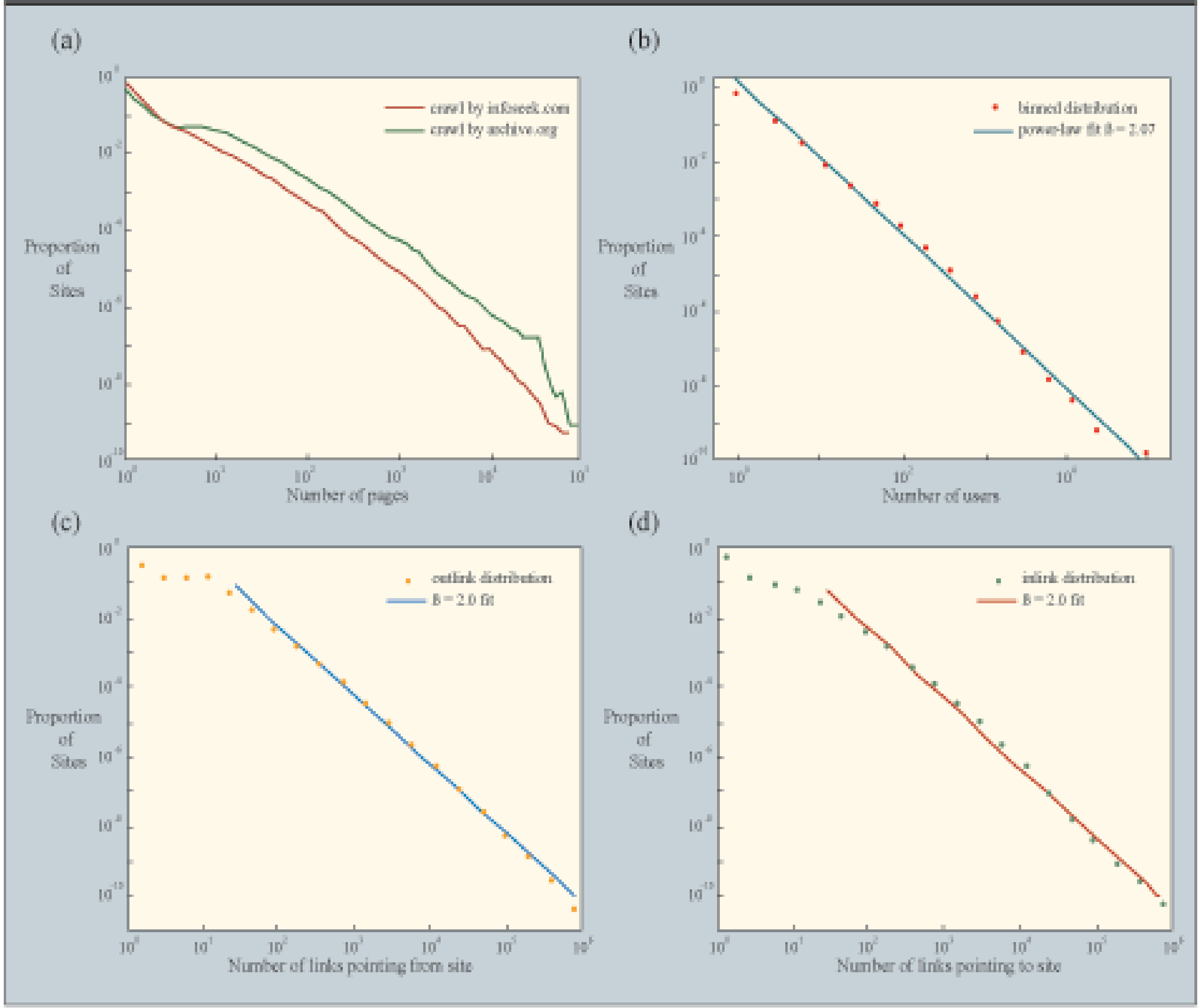


Figure 3: An alternative model of a small world, in which there are a small number of individuals who are connected to many widely-distributed acquaintances.

NETWORK ANALYSIS: POWER LAWS

Figure 2. Fitted power law distributions of the number of a site's (a) pages, (b) visitors, (c) outlinks, and (d) inlinks.



L. Adamic and B. Huberman, "The Web's Hidden Order", *CACM* 44:9, 2001

EMERGENCE IN DISCRETE DYNAMICAL SYSTEMS

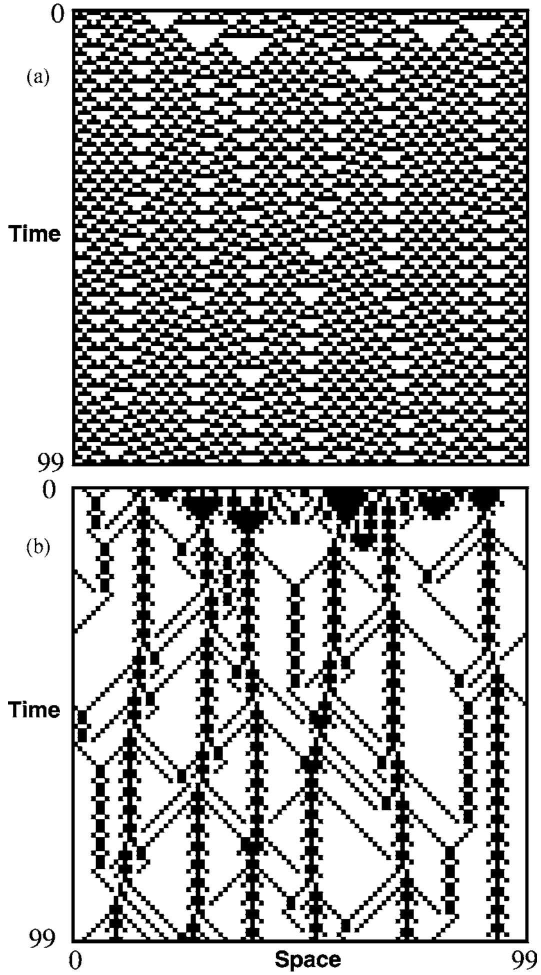


Fig 2. (a)Raw space-time diagram and (b) ltered space-time diagram of ECA 54 behavior starting from an arbitrary initial conguration. After [22].

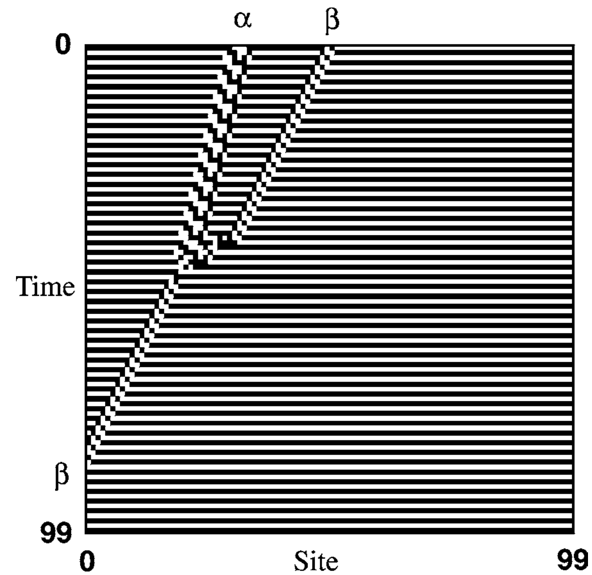


Fig 6. The interaction between an and a particle in $sync_1$.

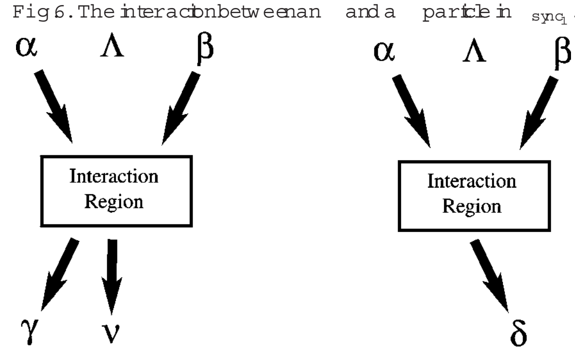
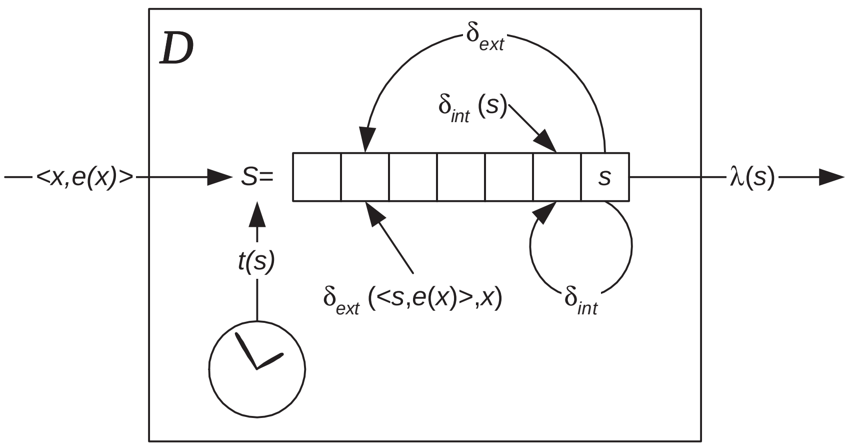


Fig. 1. Interactions between an and a particle with domain lying between.

W Hordijk, CR Shalizi, and JP Crutchfield, "Upper Bound on the Products of Particle Interactions in Cellular Automata", Physica D 154, 240-258, 2001

DISCRETE DYNAMICAL SYSTEMS: COLLECTIVE AUTOMATA MODELS

- For representing arbitrary classes of discrete dynamical systems: discrete input, output, state, transfer functions
- Hierarchical scaling
- Temporal modeling: concurrency, parallelism
- E.g. DEVS



COLLECTIVE AUTOMATA: SEQUENTIAL DYNAMICAL SYSTEMS

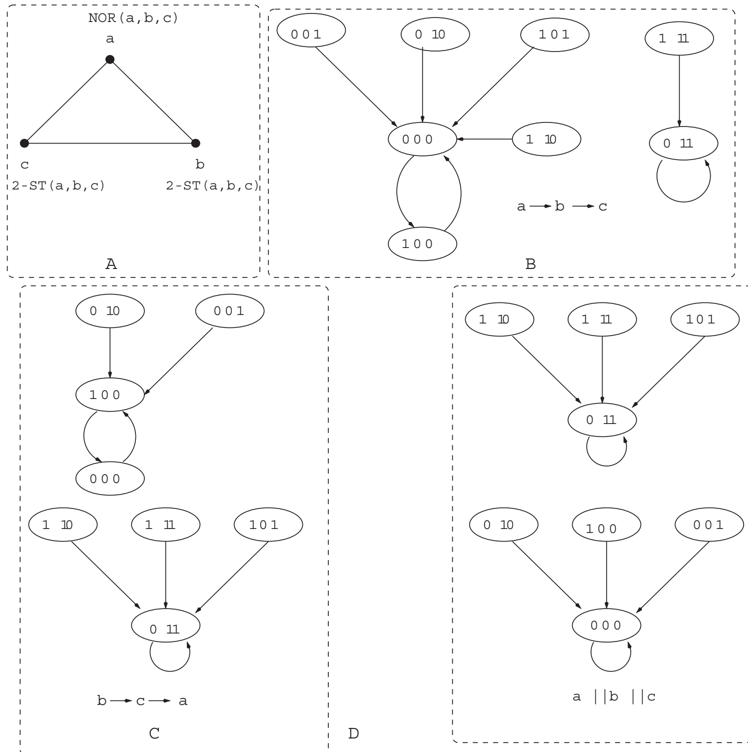


Figure 2: Example of an SDS and its phase space. Figure A shows the underlying graph and the local transition functions. Each conguration is specied as a triple (s_a, s_b, s_c). Figure B shows the phase space with $\pi = \langle a, b, c \rangle$. Figure C shows the phase space with $\pi = \langle b, c, a \rangle$. Finally, Figure D shows the phase space when all the nodes are updated in parallel (as in CA).

C. Barret *et al.*, "Reachability Problems for Classes of Sequential Dynamical Systems", submitted 2001

BEYOND DYNAMICAL SYSTEMS

Limitations of Dynamical Systems:

- Chaotic indeterminacy
- Computational complexity
- *A priori* fixed state spaces: handle evolution as nonstationarity, complex nondeterminism?

Agent-Based Approaches: e.g. Swarm

- Interactions of a large number of systems
- Considered as autonomous
- Empirical exploration of non-analytical systems

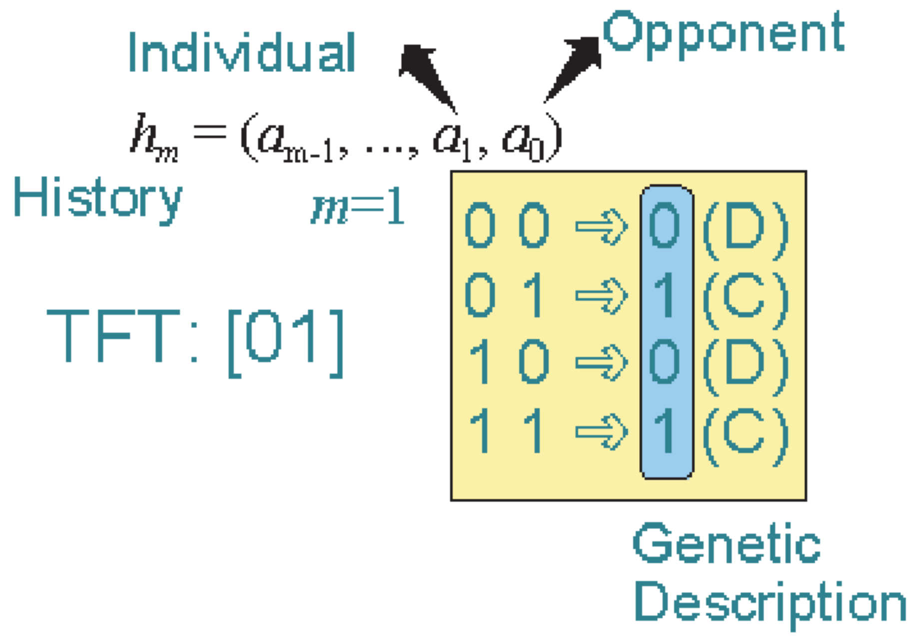
Component Systems:

- Initial set of discrete components
- Indefinitely extandable combinations
- **Examples:** Biochemistry, genetics, formal and natural language, ULNs?

Kampis, George: (1991) *Self-Modifying Systems*, Pergamon, Oxford

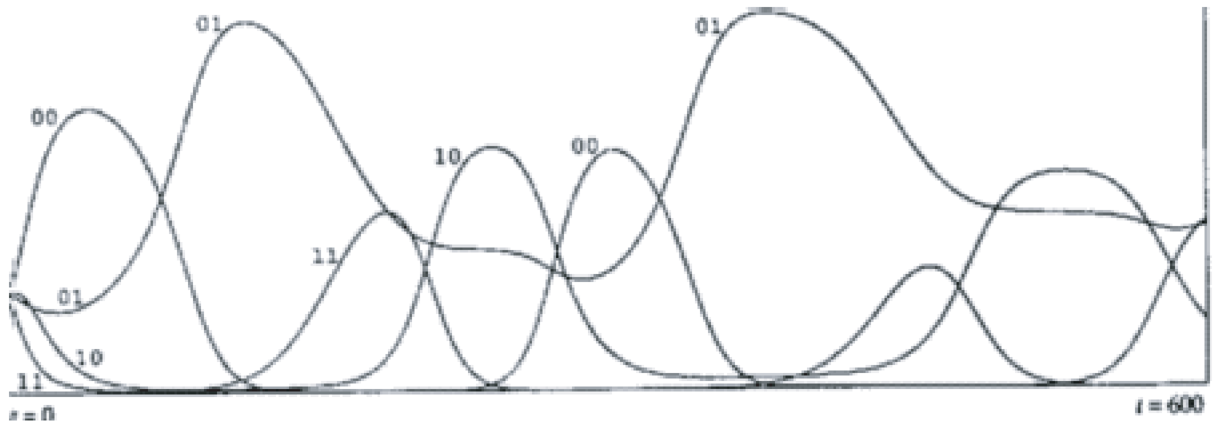
CONSEQUENCES: LEARNING AND GROWING AUTOMATA

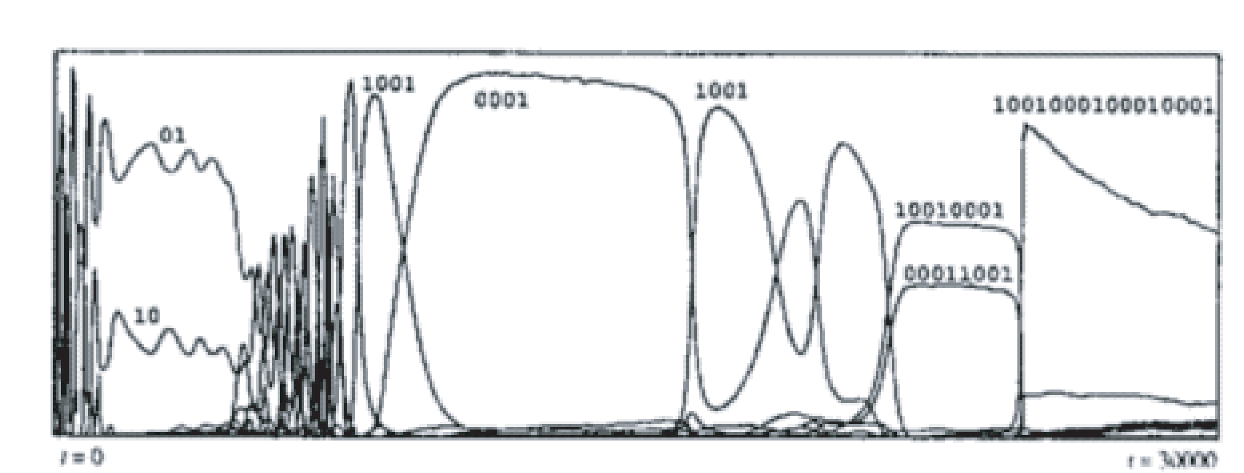
- Iterated prisoner's dillema
- Memory of opponent's n prior behaviors
- Initial random distribution of strategies
- Point mutations
- Doubling the memory: $n \mapsto 2n$
- Splitting the memory: $n \mapsto n/2$



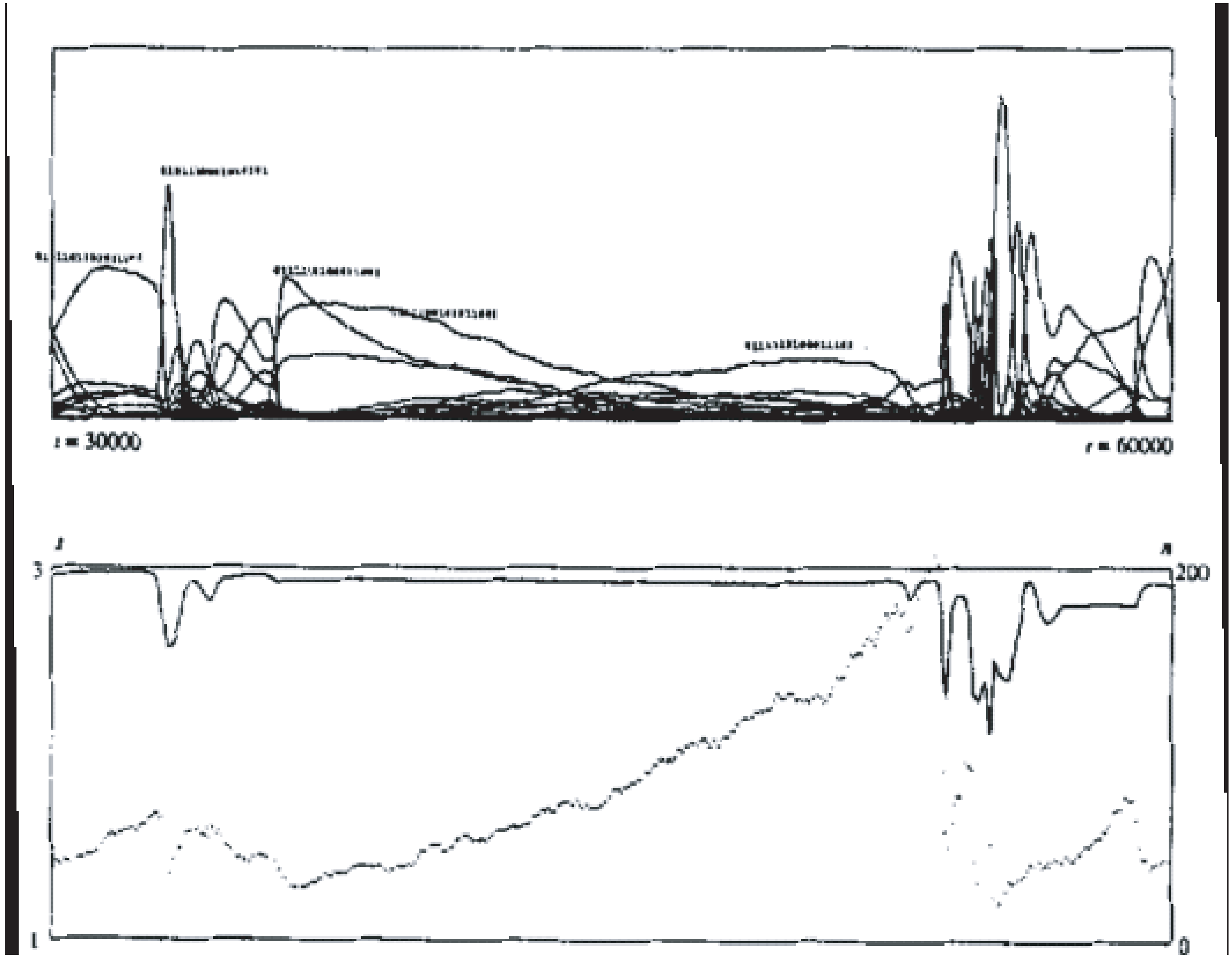
K Lindgren, "Evolutionary Phenomena in Simple Dynamics", In: *Artificial Life II*, Langton *et al.* (Eds), Addison-Wesley, 1991

LINDGREN RESULTS



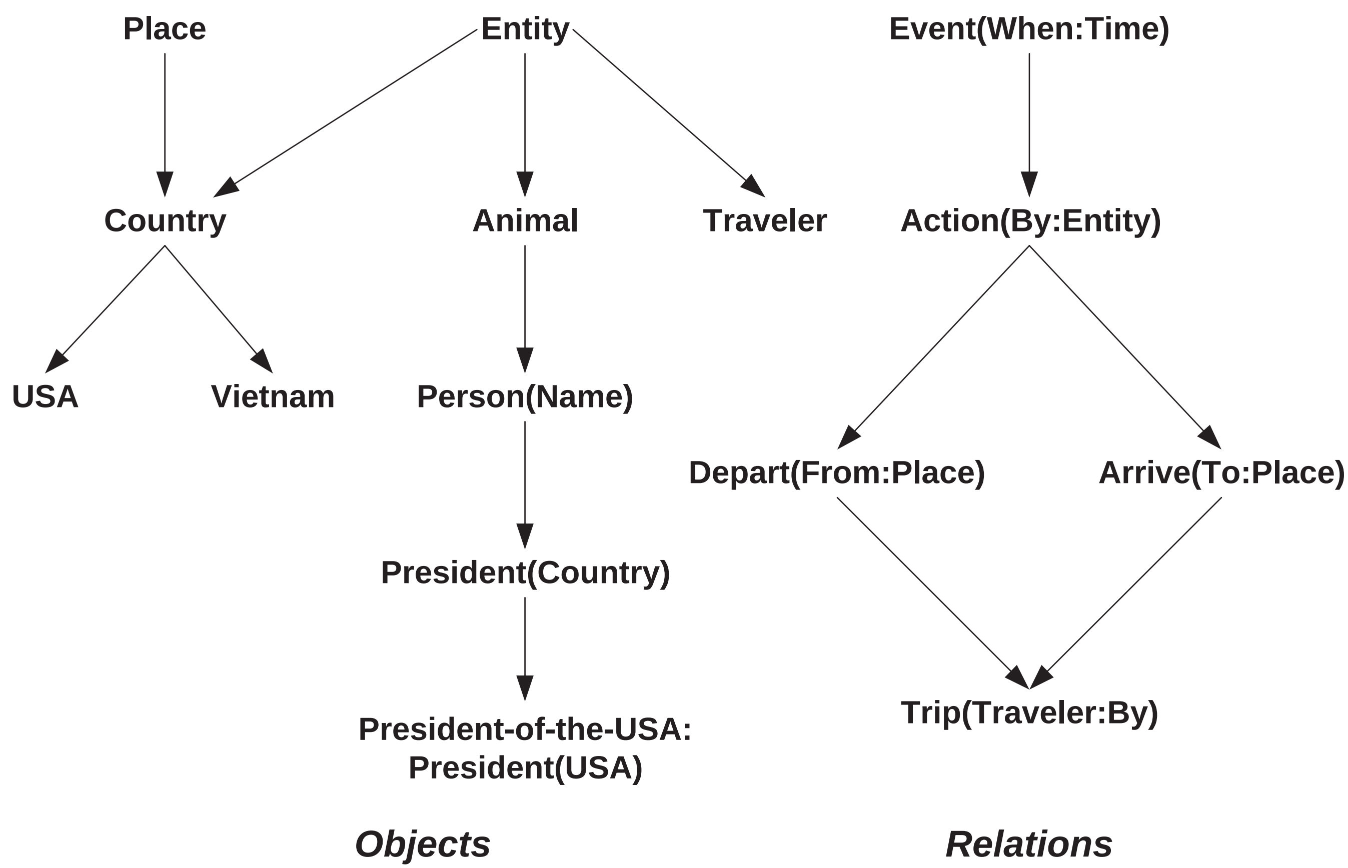


LINDGREN RESULTS



SEMANTIC OR ONTOLOGICAL NETWORKS

- Ontological database: interacting hierarchies of objects and relations
- Description logics
- Optimized for agent interaction



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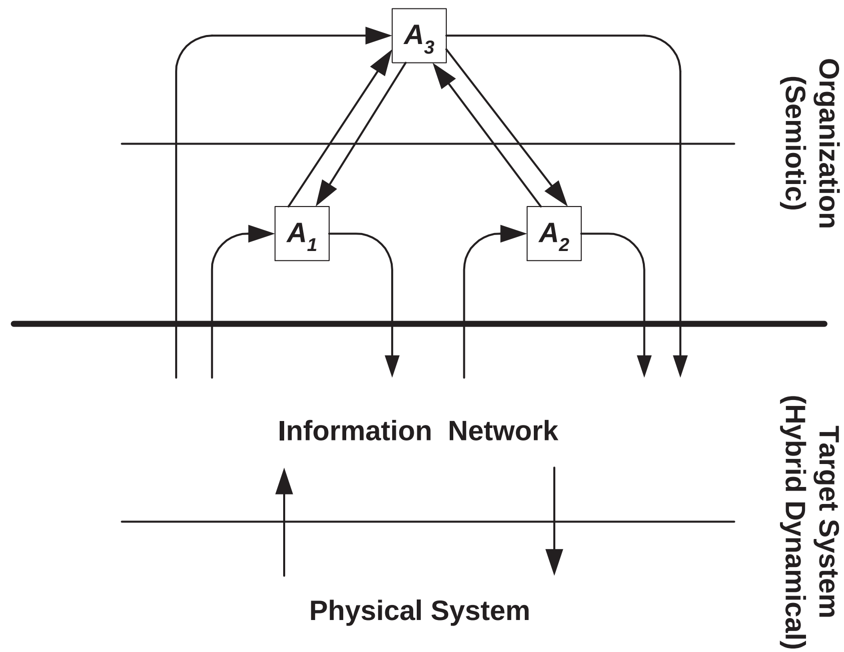
TOWARDS SEMIOTIC AGENTS

- ULNs will be interacting with physical systems and communities of interpreting agents
- Shannon's observation: really "Communication Theory", since "information" is about *interpretation*
- "Man in the loop", hybrid control model
- *Represent spaces of codes in agents*
- Semiotic theory, category theory



J Goguen "An Introduction to Algebraic Semiotics, with Applications to User Interface Design", in *Computation for Metaphor, Analogy and Agents*, ed. Chrystopher Nehaniv, Springer LNCS, v. 1562, pp. 242-291, 1999