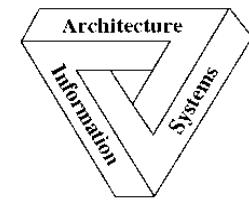


Complex Adaptive Systems: Emergence and Self-Organization

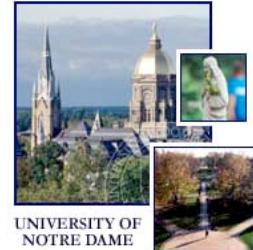
**Tutorial Presented at HICSS-42
Big Island, HI
January 5, 2009**

Stephen H. Kaisler, D.Sc. And Gregory Madey, Ph.D.





Who we are



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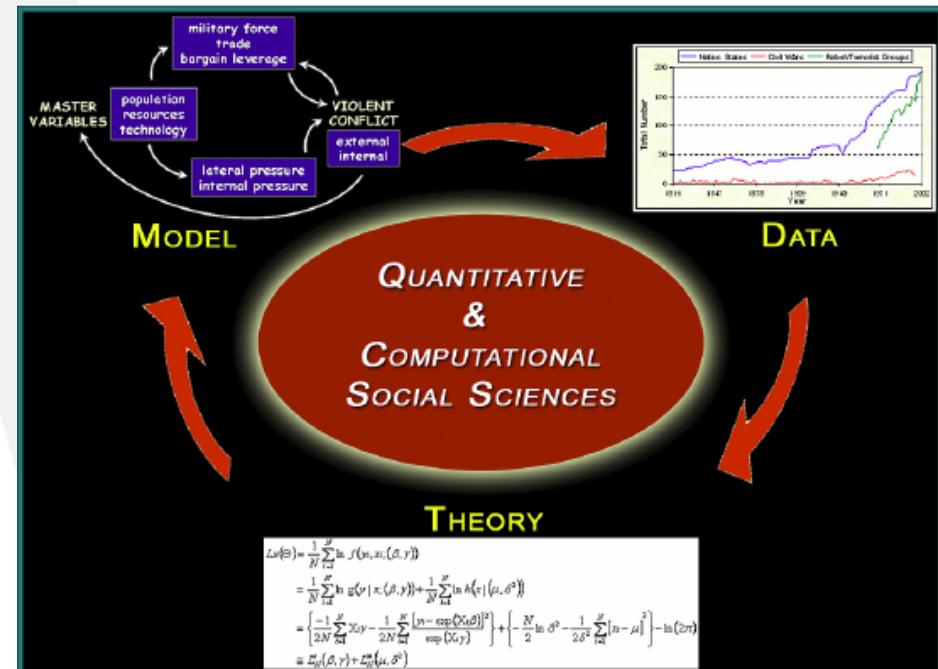
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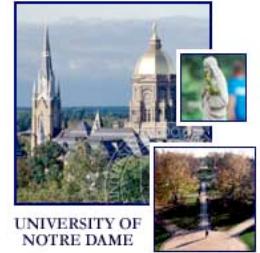


Source: Popp 2005



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Agenda

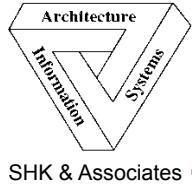


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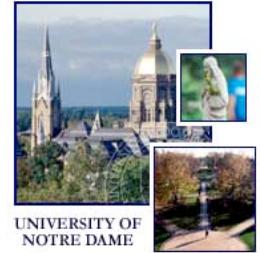
Session

Time

- | | | |
|------|--|-------------|
| I. | Introduction to Complex Adaptive Systems | 9:00 – |
| | 10:15 Break | |
| II. | Emergence & Self-Organization | 10:45 – |
| | 12:00 Lunch | |
| III. | Tools, Techniques & Analysis | 1:00 – 2:15 |
| | Break | |
| IV. | CAS Examples & Applications | 2:45 – 4:00 |



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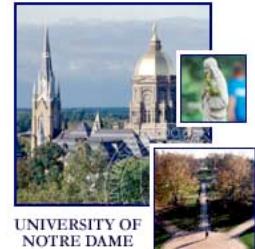
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A (Brief) Introduction To Complex Adaptive Systems



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I. Introduction



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Complex, Adaptive Systems:

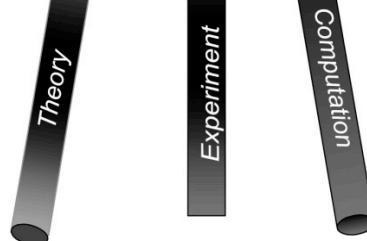
Exhibit behaviors arising from non-linear spatio-temporal interactions among a large number of components and subsystems.

Proposition:

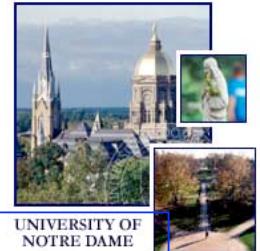
CAS studies indirect effects. Problems that are difficult to solve are often hard to understand because the causes and effects are not obviously related. Pushing on a complex system "here" often has effects "over there" because the parts are interdependent.

Takeaway:

CAS is a viable method for modeling complex physical and social systems to understand their behavior based on observed data.



What is Complexity?

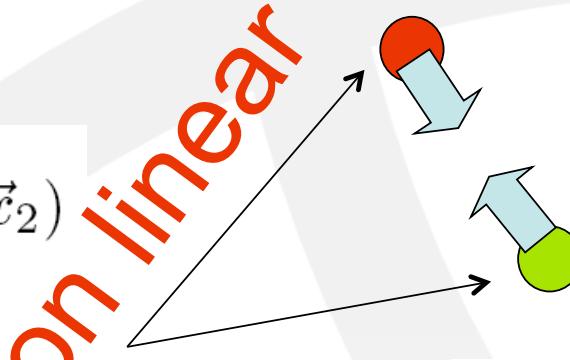


- π Complex: consisting of interconnected or interdependent parts
 - Not easy to understand or analyze
- π Simple systems: An oscillator, a pendulum, a spinning wheel, an orbiting planet
- π Complex Systems: Government, an economy, families, the human body—physiological perspective, a person—psychosocial perspective, the brain, the ecosystem of the world
- π Not Shannon, Turing, or Kolmogorov

$\frac{d\vec{p}_1}{dt} = \vec{F}_{2/1}(\vec{x}_1, \vec{x}_2)$

$\frac{d\vec{p}_2}{dt} = \vec{F}_{1/2}(\vec{x}_1, \vec{x}_2)$

non linear



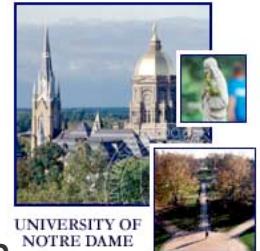
$G m_1 m_2 \frac{\vec{x}_2 - \vec{x}_1}{|\vec{x}_1 - \vec{x}_2|^3}$

$G m_1 m_2 \frac{\vec{x}_1 - \vec{x}_2}{|\vec{x}_1 - \vec{x}_2|^3}$



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Why Define Complexity?



- π To estimate how long a particular system will take to solve a problem
- π To estimate difficulty in engineering complex systems
- π To understand the limits of prediction, approximation, and simulation
- π To answer fundamental scientific questions
- π Does complexity increase through evolution – biological or otherwise?

“As evolution proceeded on the surface of the earth, there has been a progressive increase in size and complexity”

- J. T. Bonner Evolution of Complexity.

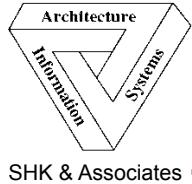
“Evolution tends to push systems towards the edge of chaos, where complex, interesting behaviors such as life can occur? “

- Chris Langton

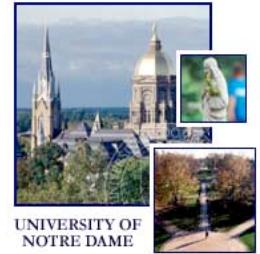
“The universe, the biosphere, the econosphere have all become more complex”

- Stuart Kauffmann

Can we quantify the increase in complexity over time?

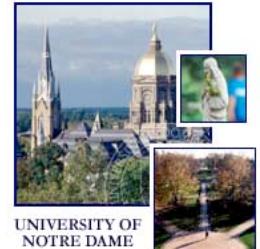


This is not Complexity!



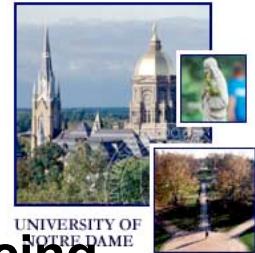
One Thousand monkeys typing away are not going to recreate Shakespeare!

Complexity vs. Complicated



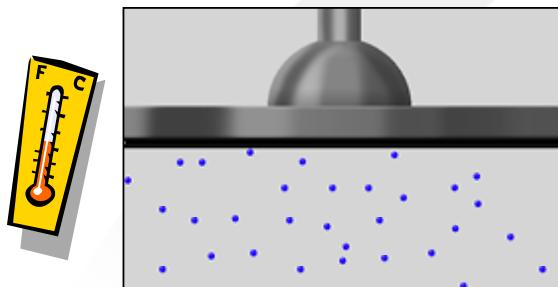
- π **Complexity is difficult to describe**
- π **If we say something is complex in ‘everyday’ language we mean something that is difficult or impossible to understand with simple logic (i.e., long term weather patterns)**
- π **A car is not complex, just *complicated*.**
 - Cars do exhibit “unwanted functionality”
- π **Complicated Systems: Often difficult to describe, but succumb to divide-and-conquer approaches.**
- π **Complicated is easier to cope with than complex – Seth Bullock**
 - Numerous techniques to resolve complicated systems
 - As a last resort, use brute force/trial and error
- π **But, complicated systems are often complex:**
 - Software does suffer from “emergent” bugs!!

Explanation vs Prediction

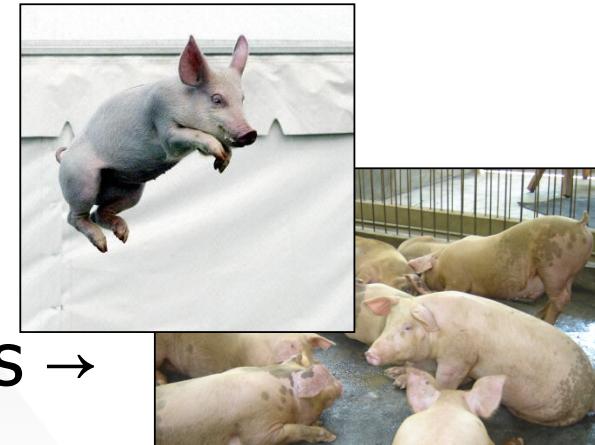


- π Low-level behavior is unpredictable (gas molecules bouncing around, pigs pigging about)
- π We can explain how more gas increases temperature (ideal gas law) but not easy to explain how more pigs brings about an abrupt phase transition in pig violence
- π For simple (linear) systems:
 - a small change to a system's components → a small change at the system level
- π For complex (non-linear) systems:
 - a small change to a system's components → large/small/no change at the system level

From Seth Bullock, Introduction to Complexity Science, 2006



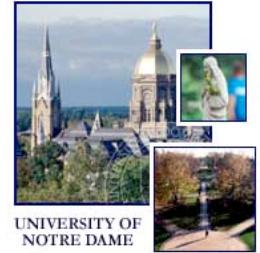
← Simple Gas
Complex Pigs →





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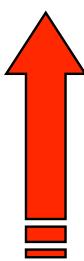
Complexity Issues



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Law of Large
Numbers
 $\epsilon \sim (n)^{** 1/2}$

Quantity of Objects



Randomness

Complexity



Combinatoric
Exponential
Explosion

- π Complex behaviour originates from the operation of simple underlying rules (Simon's conjecture).
- π But, sometimes, deducing behaviour from rules is not possible.
- π There is no practical way to study the network of causality in detail.
- π Therefore, we need ways to synthesize understanding from large state spaces and multidimensional meshes
- π However, the spectre of computational intractability haunts the space between rules and consequences.

MACRO

2) Unorganized
Complexity
(Aggregates)

MICRO

1) Organized
Simplicity
(Machines)

MESO

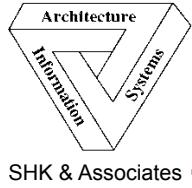
3) Organized
Complexity
(Systems)

Law of Medium Numbers is...
Murphy's Law

From: G.M. Weinberg, An
Introduction to General Systems
Thinking,
John Wiley & Sons, New York, 1975,
p 18.

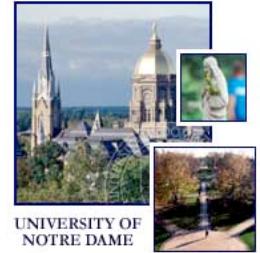


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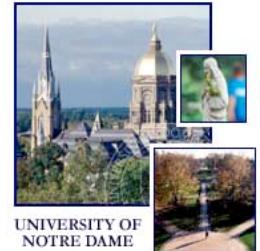
What is a System?



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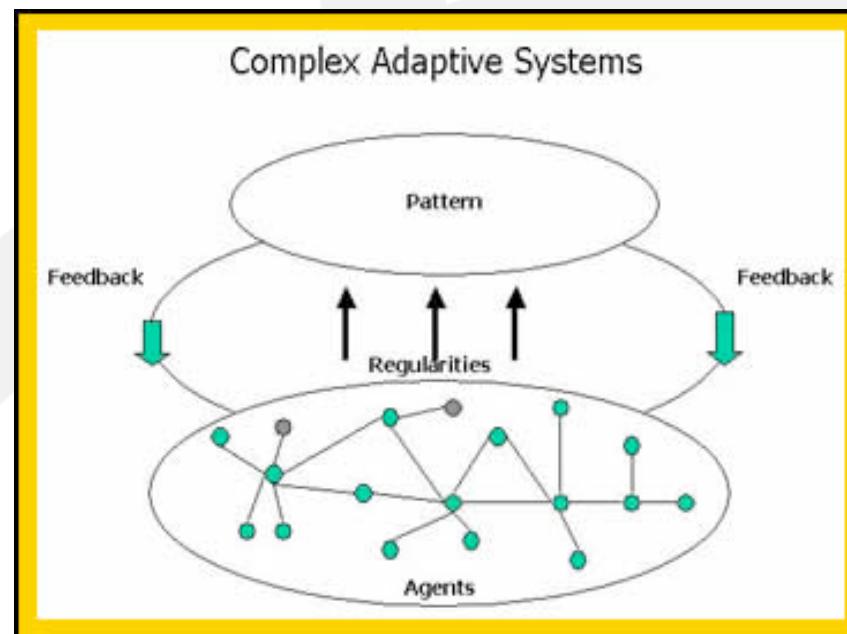
- π **A system is a purposeful collection of interrelated Components that work together to achieve some objective**
- π **Many types of systems: physical, political, biological, social, ...**
- π **We are primarily interested in sociotechnical systems:**
 - technical system + knowledge of goals to achieve (operational processes + people involved)
- π **Complex systems exhibit four characteristics:**
 - Self-organization
 - Non-linearity
 - Order/Chaos Dynamic
 - Emergence
- π **Further complexity ensues by allowing a system to *adapt* to its environment**

Complex Systems

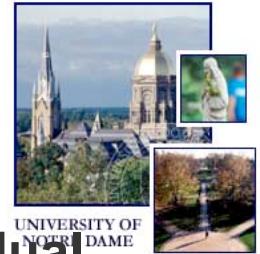


π A **complex system** is any system:

- That involves a (large) number of elements, arranged in structure(s) which can exist on many scales
- These elements interact locally: every element is connected to every element in the system, even indirectly
- Structures go through a process of change not describable by a single rule or reducible to a single level of explanation
- Features emerge that cannot be predicted from the current description of the structure(s)



What are Complex Systems?



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π **At their lowest level, they are comprised of a set of individual agents (a general term!)**

- Agents are *heterogeneous*, differing in important characteristics.
- Agents are *indivisible*
- Agents are/may be *organized* into some sort of group or hierarchy, which is/may be structured. These organizational structures in turn influence system dynamics.

π **The system is *dynamic* – it changes over time:**

- The agents interact, adapt and undergo natural selection in response to their own environment. The system dynamics are *non-linear*.
- Agent change often occurs in response to *feedback* from their actions.

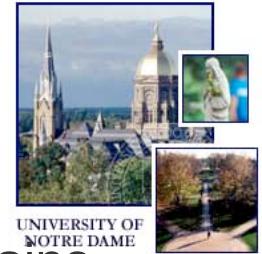
π **Complex systems may possess the characteristic of emergence.**

- The macro- or system-level behavior that emerges from the activities and behaviors of the component parts of the system, but which cannot be explained at the agent level alone.
- It's usually the system-level behavior that intrigues us.

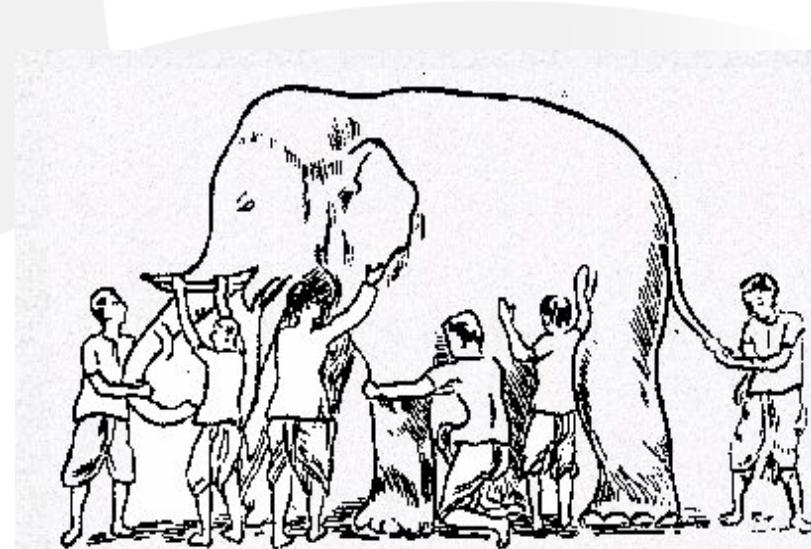


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Complex Systems Theory

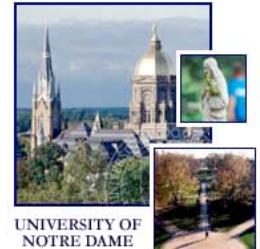


- π **Complex Systems Theory** is a scientific framework that explains how rules govern emergence and the constraints mediating self-organization and system dynamics.
- π The science of complexity, is not a single body of theory, but rather is comprised of a collection of fields, including:
 - *Artificial Intelligence (AI)*
 - *Cognitive science*
 - *Ecology*
 - *Evolution*
 - *Game theory*
 - *Linguistics*
 - *Social science*
 - *Artificial Life*
 - *Computer science*
 - *Economics*
 - *Immunology*
 - *Philosophy*





Some Measures of Complexity



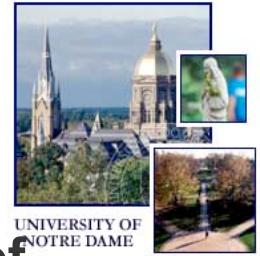
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- π Computational complexity:
 - How long a program runs (or how much memory it uses).
 - Asymptotic.
- π Language complexity (Formal Language Theory):
 - Classes of languages that can be computed (recognized) by different kinds of abstract machines.
 - Decidability, computability.
- π Information-theoretic approaches (after Shannon and Brillouin):
 - Algorithmic Complexity (Solomonoff, Komogorov, and Chaitin):
 - Length of the shortest program that can produce the phenomenon.
 - Mutual information (many authors)
- π Logical depth (Bennett).
- π Thermodynamic depth (Lloyd and Pagels)



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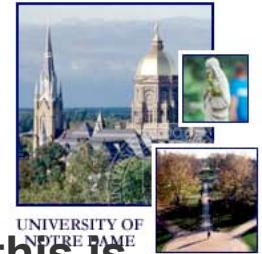
Adaptive Systems



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- π An *adaptive system* is a system that changes in the face of perturbations so as to maintain some kind of invariant state by altering its properties or modifying its environment:
 - Perturbations = changes in environment
 - Invariant = such as ‘survival’
 - Property = such as behavior or structure
- π The *ability* to adapt depends on the observer who chooses the scale and granularity of description
- π An adaptive system is necessarily complex, but the obverse is not necessarily true.
- π Evolution is a result of an adaptive system

Kinds of Adaptation

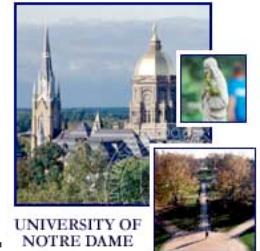


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- π **Task-based:** changes that allow the completion of a goal when this is challenged.
 - Artificial systems
- π **Sub-organismic:** a system/mechanism within the organism that maintains some internal property
 - Ex. homeostasis in individual cells, etc.
 - Can give rise to organismic level phenomena such as habituation (which may be non-adaptive at this higher level)
- π **Organismic:** changes that maintain essential properties of the organism
 - those that guarantee survival, identity, autonomy
- π **Ecological:** changes that maintain certain patterns of behaviour of one or many organisms.
 - Recovery of sensorimotor invariants and habitual behaviour (group, social norms)
 - Radical adaptation to body reconfiguration.
- π **Evolutionary:** changes in distribution of phenotypes due to differential rates of survival and reproduction. Resulting phenotypic properties can be said to be adapted. Occurs at population level.



Approaches To CAS



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Considering complex adaptive systems, we are interested in:

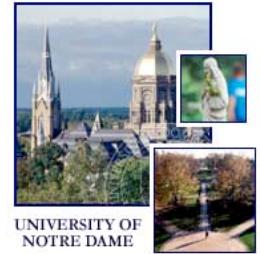
1. how interactions give rise to patterns of behavior
2. understanding the ways of describing complex systems
3. how complex systems form through pattern formation and evolution
4. how complex systems adapt to their changing environment

How to measure a system's complexity?

- By its unpredictability?
- By how difficult it is to describe?
 - No single model adequate to describe system---the more models that are required, the more complex the system. (Lee Segel)
- By measuring how long before it halts, if ever? By how long until it repeats itself?
- Entropy?
- Multiple levels of organization?
- Number of interdependencies?



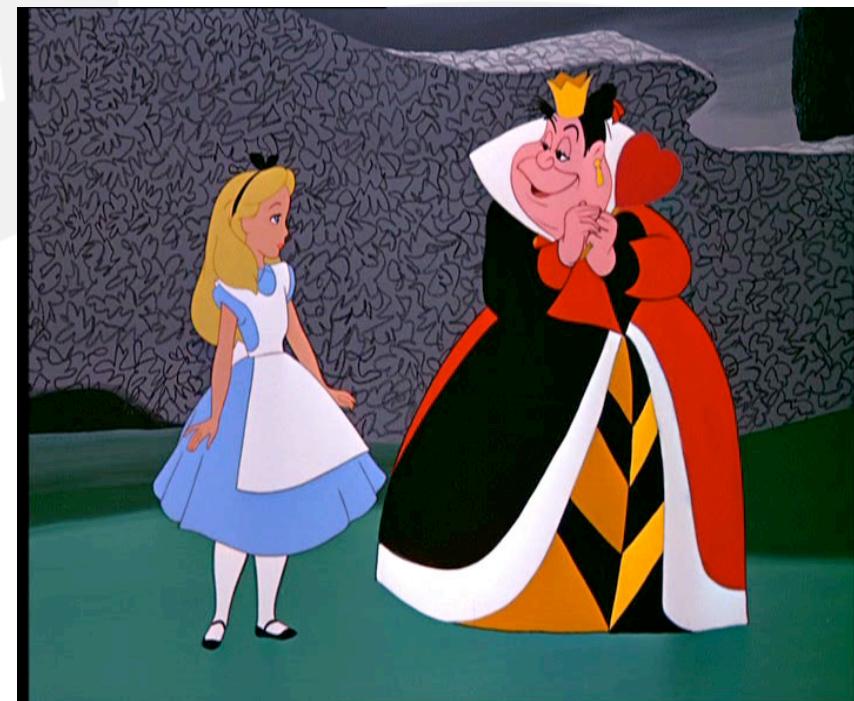
A little reflection ...



Alice Laughed: "There's no use trying," she said; "one can't believe impossible things.

"I daresay you haven't had much practice," said the Queen.
"When I was younger, I always did it for a half hour each day. Why, sometimes I've believed as many as six impossible things before breakfast."

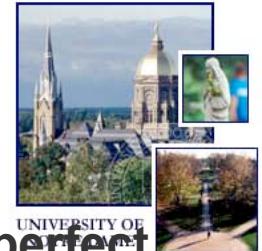
- Lewis Carroll, *Alice in Wonderland* -





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CAS: Characteristics



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π **Sub optimal:** A complex adaptive systems does not have to be perfect in order for it to thrive within its environment.

- It only has to be slightly better than its competitors and any energy used on being better than that is wasted energy.
- A CAS, once it has reached the state of being good enough, will trade off increased efficiency every time in favor of greater effectiveness.

π **Requisite Variety:** The greater the variety within the system the stronger it is.

- Ambiguity and paradox abound in complex adaptive systems which use contradictions to create new possibilities to co-evolve with their environment.
- Democracy is a good example in that its strength is derived from its tolerance and even insistence in a variety of political perspectives.

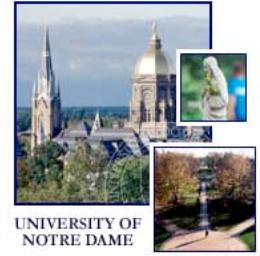
π **Connectivity:** The ways in which the agents in a system connect and relate to one another is critical to the survival of the system.

- It is from these connections that the patterns are formed and the feedback disseminated.
- The relationships between the agents are generally more important than the agents themselves.



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CAS: Characteristics



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π

Simple Rules:

- Complex adaptive systems are not complicated. The emerging patterns may have a rich variety, but like a kaleidoscope the rules governing the function of the system are quite simple.
- A classic example is that all the water systems in the world, all the streams, rivers, lakes, oceans, waterfalls etc with their infinite beauty, power and variety are governed by the simple principle that water finds its own level.

π

Iteration:

- Small changes in the initial conditions of the system can have significant effects after they have passed through the emergence - feedback loop a few times (often referred to as the butterfly effect).
- A rolling snowball gains on each roll much more snow than it did on the previous roll and very soon a fist sized snowball becomes a giant one.

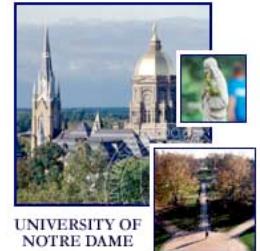
π

Self-Organizing:

- There is no hierarchy of command and control in a complex adaptive system.
- There is no planning or managing, but there is a constant re-organizing to find the best fit with the environment.
- A classic example is that if one were to take any western town and add up all the food in the shops and divide by the number of people in the town there will be near enough two weeks supply of food, but there is no food plan, food manager or any other formal controlling process. The system is continually self organizing through the process of emergence and feedback.



CAS: Characteristics



π Edge of Chaos:

- Not the same as chaos theory, which is derived from mathematics.
- Systems exist on a spectrum ranging from equilibrium to chaos.
- A system in equilibrium does not have the internal dynamics to enable it to respond to its environment and will slowly (or quickly) die.
- A system in chaos ceases to function as a system.
- The most productive state to be in is at the edge of chaos where there is maximum variety and creativity, leading to new possibilities.

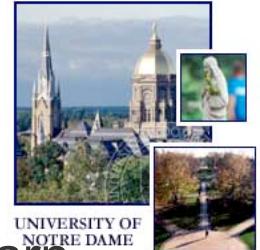
π Nested Systems:

- Most systems are nested within other systems and many systems are systems of smaller systems.
- Consider a food shop. The shop is itself a system with its staff, customers, suppliers, and neighbours.
- It also belongs to the food system of that town and the larger food system of that country. It belongs to the retail system locally and nationally and the economy system locally and nationally, and probably many more.
- Therefore it is part of many different systems most of which are themselves part of other systems.



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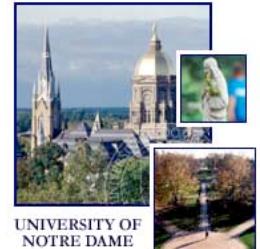
Complex Evolving Systems



- π Some people suggest that these type systems continuously learn.
- π As Pogo has said (paraphrased):
“We have met the future and they are us!” (we, as humans, continuously evolve, not physically in our lifetimes, but emotionally, cognitively, etc.)
- π CASs continuously adapt to the changes around them but do not learn from the process.
- π CESs learn and evolve from each change enabling them to influence their environment, better predict likely changes in the future, and prepare for them accordingly.



What's The Social Science Problem?

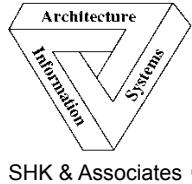


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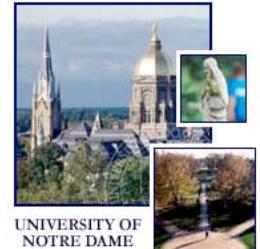
- π Most pre-computational social science models are linear:
 - Linearity is based on independence of elements
 - Linearity is a good modeling technique for simple systems
 - The linearity assumption implies that the whole is equal to the sum of its parts!
- π We know a lot about:
 - Individuals (through surveys)
 - Aggregated as groups and populations
 - On a domain-specific basis
- π We know a lot less about interactions among individuals and groups:
 - How social structures form; how protocols emerge and the interactions in large groups and among subgroups
 - How and why do group structures (and their protocols) change
 - What the content of interaction is: influence, power, imitation, exchange, association

BUT:

- π Social science systems are not simple,....
- π The whole may be greater (or lesser) than the sum of its parts!!
- π Modeling the dynamics is (very) hard ...



Why is the Study of CAS Important?



π Problem of *Computational Irreducibility*:

The failure of mathematical models to provide explicit solutions to complex phenomena



Position and velocity
can be calculated
exactly

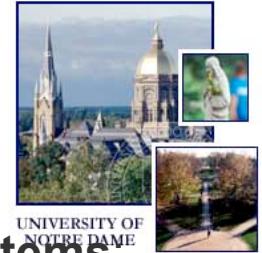


Human behaviour is
computationally Irreducible



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Studying CAS



π Multi-scale descriptions are needed to understand complex systems.

- Complexity arises at different levels
- Mathematical tools must scale
- Need to understand behavior propagation across levels
- Ex: Weather - (cyclones, tornadoes, dust devils)

π Fine scales influence large scale behavior:

- Ex: Neurophysiology - a nerve cell action triggering a muscle
- Ex: Economy/society - the relevance of individuals to larger scale behaviors

π Pattern Formation:

- Ex: weather - cells of airflow
- Ex: Economy/society - patterns of industrial/residential/ commercial areas (for example, Schelling)

π Multiple (meta)Stable States:

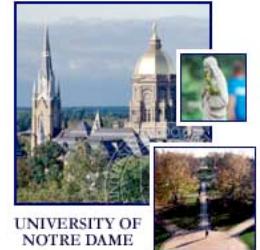
- Small displacements (perturbations) lead to recovery; larger ones can lead to radical changes of properties.

Ref: NECSI, <http://www.necsi.edu/guide/points.html>



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Studying CAS



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π Finding a Metric of Complexity:

- The amount of information necessary to describe the system.
- The apparent complexity depends on the scale at which the system is described

π Behavior Complexity:

- How to describe the behavior (actions) of a system acting in response to its environment, where the complexity of the environmental variables are $C(e_i)$ and of the behavior is $C(b)$
- The behavior is $b = f_b(e_i)$, so the goal is to determine the nature of f_b
- Bar-Yam suggests: $C(f_b) = C(b)*2^{C(e(i))}$
 - Is this behavior impossible to determine except for the simplest environments?

π Emergence:

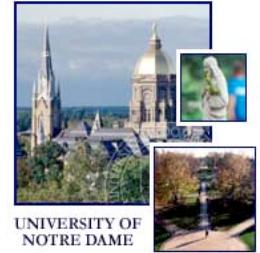
- Parts must be studied "in vivo".
- Ex (after Bar-Yam): "If you remove a vacuum tube from a radio and the radio squeals do not conclude that the purpose of the tube is to suppress squeals."
- The nature of complex systems can be assessed by investigating how changes in one part affect the others, and the behavior of the whole

Ref: NECSI, <http://www.necsi.edu/guide/points.html>



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Studying CAS



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π 7+/-2 Rule (Miller 1956):

- For a system divided into components, looking at the dependencies between them, when does the state / behavior of one of the components depend on the state of each of the other ones, and not on an average.
- When does the central limit theorem applies to a number of independent variables (Bar-Yam)
- Much empirical evidence: structure branching ratios in proteins, physiology, brain, and social systems

π Composition:

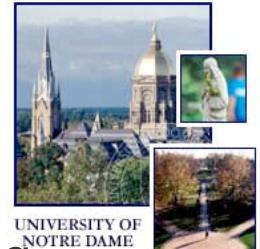
- To form a new complex system take parts (aspects) of other complex systems and recombine them.
- Composites allow rapid evolution and can minimize amount of testing
- Ex: human genome, software/system engineering, creativity

π Control Hierarchy:

- When (if) a single component controls the collective behavior (not the individual behaviors of all the components) of a system, then the collective behavior cannot be more complex than the individual behavior, i.e., there is no emergent complexity.

Ref: NECSI, <http://www.necsi.edu/guide/points.html>

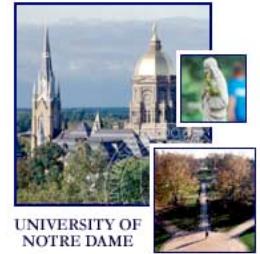
Wicked Problems



- π Wicked problems have incomplete, contradictory, and changing requirements
 - solutions to them are often difficult to recognize as such because of complex interdependencies.
- π Rittel and Webber (1973) stated that while attempting to solve a wicked problem, the solution of one of its aspects may reveal or create another, even more complex problems.
- π Complexity—systems of systems—is among the factors that makes wicked problems so resistant to analysis and, more importantly, to resolution
- π Wicked problems are adaptive, e.g., the (partial) solution changes the problem
 - Is there a restatement of Heisenberg's Hypothesis here??



Wicked Problems



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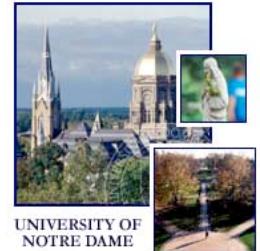
π

Characteristics (Ritchey 2005):

1. There is no definitive formulation of a wicked problem.
2. Wicked problems have no stopping rule.
3. Solutions to wicked problems are not true-or-false, but better or worse.
4. There is no immediate and no ultimate test of a solution to a wicked problem.
5. Every solution to a wicked problem is a "one-shot operation"; because there is no opportunity to learn by trial-and-error, every attempt counts significantly.
6. Wicked problems do not have an enumerable (or an exhaustively describable) set of potential solutions, nor is there a well-described set of permissible operations that may be incorporated into the plan.
7. Every wicked problem is essentially unique.
8. Every wicked problem can be considered to be a symptom of another problem.
9. The existence of a discrepancy representing a wicked problem can be explained in numerous ways. The choice of explanation determines the nature of the problem's resolution.
10. The planner has no right to be wrong (planners are liable for the consequences of the actions they generate).



Examples of Wicked Problems



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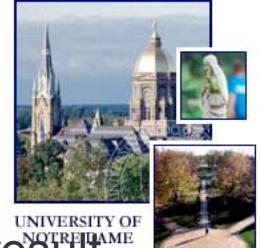
- π Global Warming
- π War on terrorism
- π Sprawl and Sustainable Development
- π A National Healthcare System for the U.S.
- π World Hunger
- π Energy Crisis: When the Oil (Coal) Runs Out?
- π Large-Scale Software Development
- π Epidemic: Worldwide Explosion of Ebola/Marburg/...
- π Emergent Systems

- π And, your favorite physical or social science problem here!!



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Some Open Questions

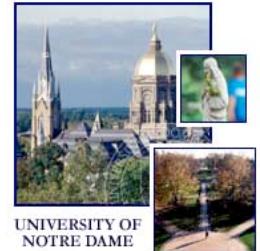


- π If we arbitrarily combine different parts of complex systems, will the result exhibit CAS properties? (Genetics, maybe yes; software, probably not)
- π If we combine different parts of complex systems, does the decision process lead to reduction in the complexity of the resulting system?
- π Bar-Yam suggests: $C(f_b) = C(b)*2^{C(e(i))}$. Is this behavior impossible to determine except for the simplest environments?
- π Is a truly complex system completely irreducible?
 - =>'s cannot derive a model w/out losing some relevant properties
 - Thus, to what extent can we make abstractions (models) of the system's interactions that faithfully reproduces its macroscopic behavior?
 - Can we explain such macroscopic behavior through a set of rules that capture the microscopic interactions?



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More Open Issues



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- π John Holland has suggested:
- 1) All *CAS* exhibit **lever points** – points where a **simple intervention causes a lasting, directed effect**.

Example: vaccines.

There is no theory that tells us where or **how to look for lever points**.

- 2) **Open-ended evolution** is typical of *CAS* – an initially simple system exhibits **increasing diversity of interaction and signaling**.

Example: ecosystems.

There are no models that exhibit **open-ended evolution**.

- 3) All *CAS* have a **hierarchical organization** of boundaries enclosing boundaries.

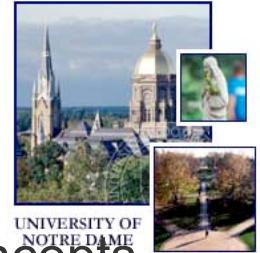
Example: biological cells.

There is no theory or general model that tells us what **mechanisms cause the formation of boundaries** in a uniform system.



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What Follows ...



- π We present three sessions that delve more deeply into the concepts of complex adaptive systems
 - Emergence & Self-Organization
 - CAS Examples
 - CAS Tools and Techniques

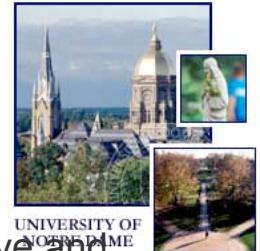


"Please, Ms. Sweeney, may I ask where you're going with all this?"

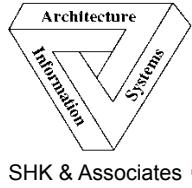


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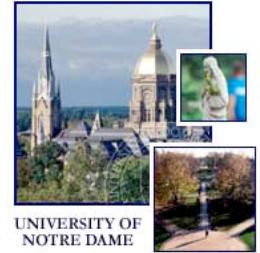
Introduction - References



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- π Grisogono, A-M. 2006. The Implications of Complex Adaptive Systems Theory for C2, DSTO, Australia
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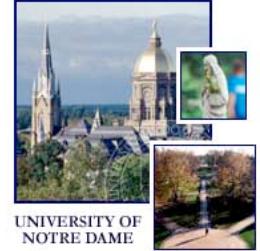
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Emergence & Self-Organization



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Emergence



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π **Emergence: Rather than being planned or controlled**

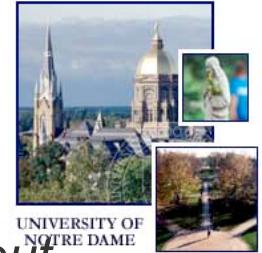
the agents in the system interact in apparently random ways.

- From these interactions patterns emerge which inform the behavior of the agents within the system and the behavior of the system itself.
- For example a termite hill is a wondrous piece of architecture with a maze of interconnecting passages, large caverns, ventilation tunnels and much more. Yet there is no grand plan, the hill just emerges as a result of the termites following a few simple local rules.



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Emergence



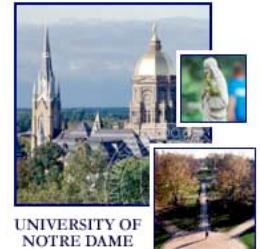
"Order is not pressure which is imposed on society from without, but an equilibrium which is set up from within."

- José Ortega y Gasset, *Mirabeau and Politics*, 1927-

- Emergent properties are characteristic of complex systems.
 - Systems of sufficient complexity will typically have properties that can't be explained by breaking the system down into its elements.
- Complex systems are self-organizing.
 - When a system becomes sufficiently complex, order will spontaneously appear.
- **Co-evolution: All systems exist within their own environment and they are also part of that environment.**
 - As their environment changes they need to change to ensure best fit.
 - But because they are part of their environment, when they change, they change their environment, and as it has changed they need to change again, and so it goes on as a constant process.



The Question of Emergence



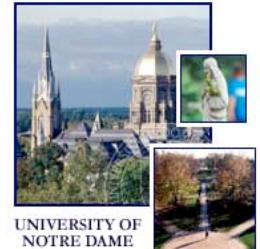
- π How come geese fly in organized V-shaped flocks, and fish swim in schools?
– Is there a leader? Maybe the one in front?





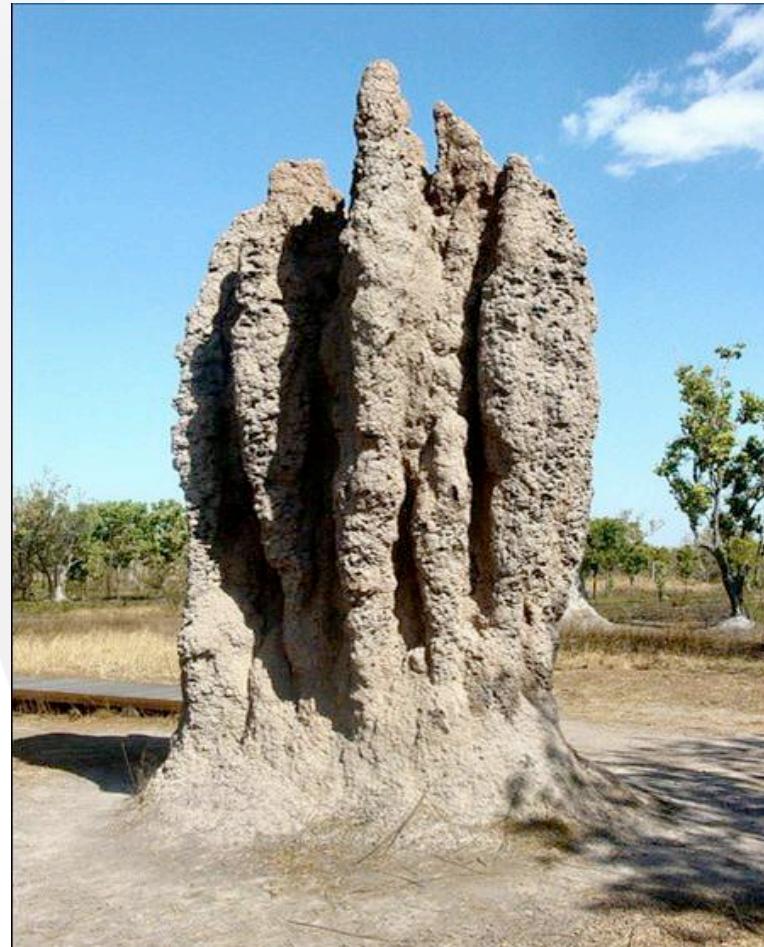
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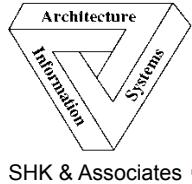
A Natural Emergent Structure



- π Ant behavior is determined by the local interactions of many ants
- π Exemplar of a “superorganism”
- π A superorganism is any aggregate of individual organisms that behaves like a unified organism.
- π Members of a superorganism have highly specialized social cooperative instincts, divisions of labor, and are unable to survive away from their superorganism for very long.

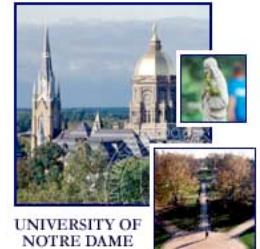
Termite Ant Cathedral Mound





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About Ants



π Consider ants:

- Simple nervous systems.
- Individual ants regarded as unconscious automatons.
- Interactions not very complex:
 - Signal in only a few (5-8) different ways.
- 30% of Amazon biomass is ants and termites
- Dry weight of social insects is 4x that of other land animals in Amazon

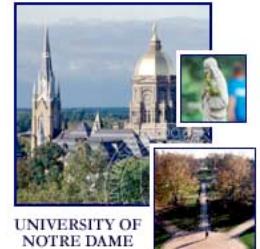
π Yet: behavior of ant colonies can be astounding.

- Colonies may contain 5,000-2,000,000 individuals.
- Behavioral repertoires include:
 - Elaborate nest construction and defense. E.g.:
 - Columnar or arch-shaped structures.
 - Wedge-shaped nests oriented N-S or E-W direction.
 - Efficient foraging behavior.
 - Slavery of other ant species.
 - Farming of fungi and aphids.



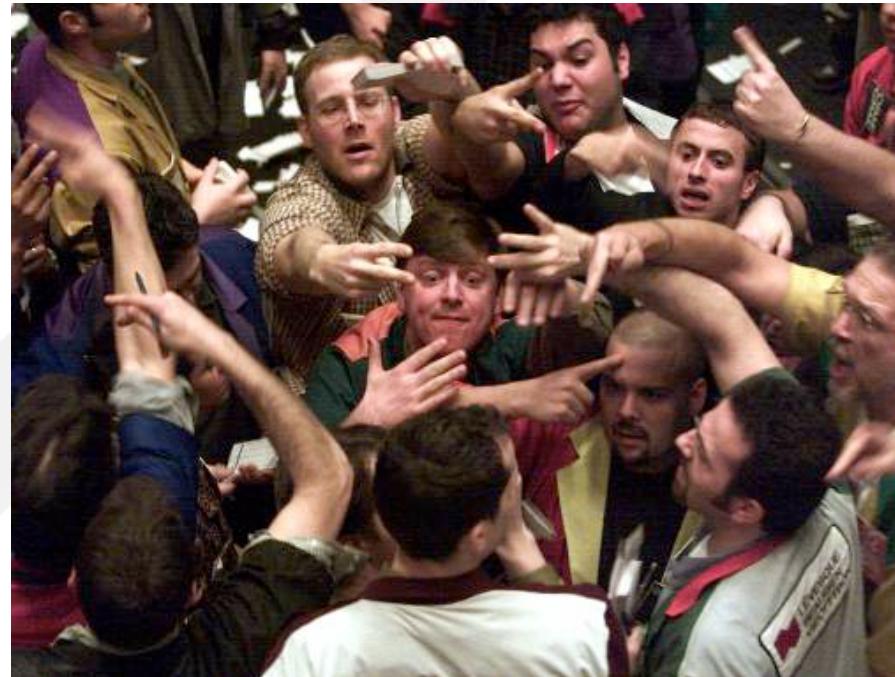
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Another Emergent Structure



π Stock Market(s):

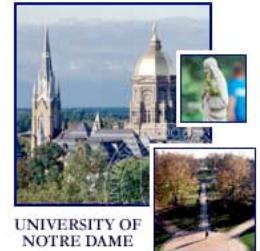
- No leader
- Each investor is an agent – has a limited knowledge of the market, has to abide by some rules
- Patterns of working of the market emerge: but how?





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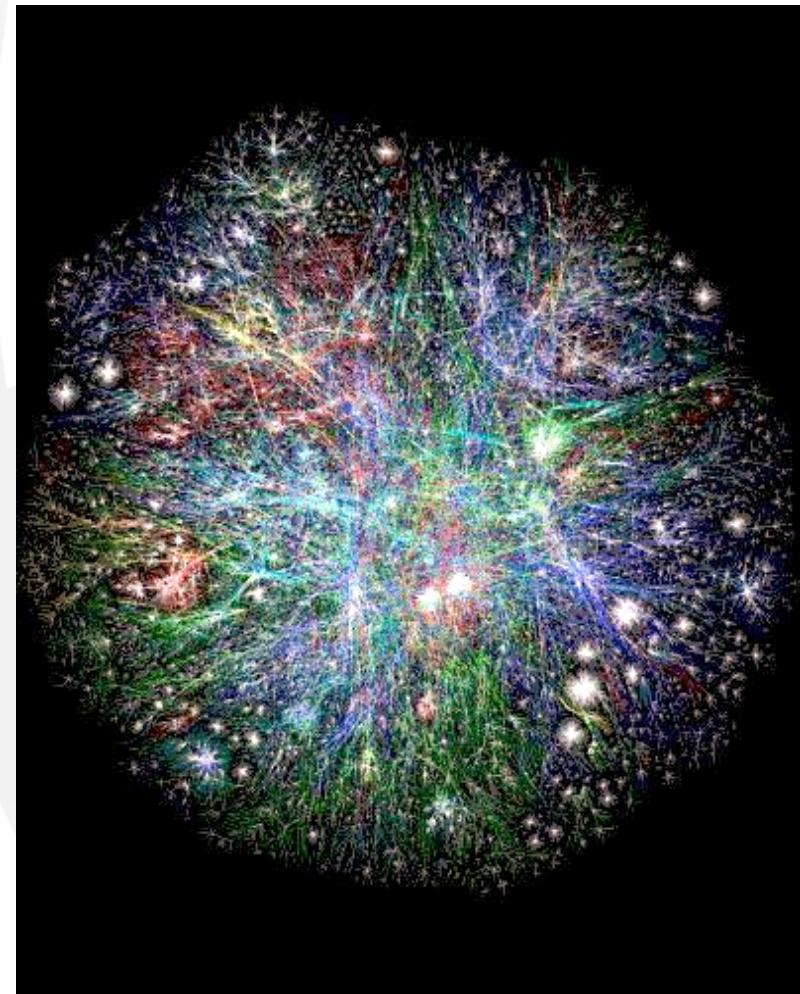
Another Emergent Structure



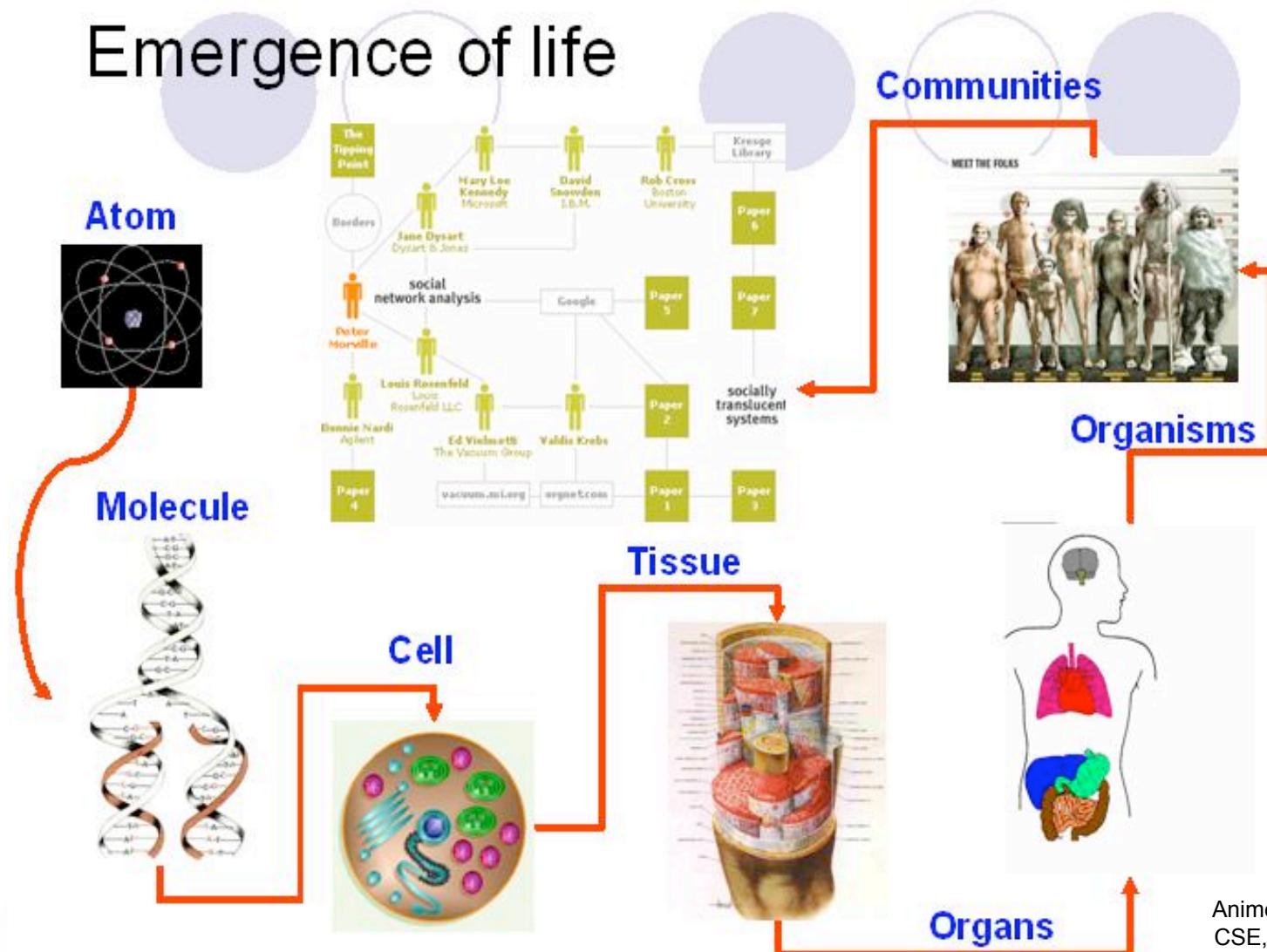
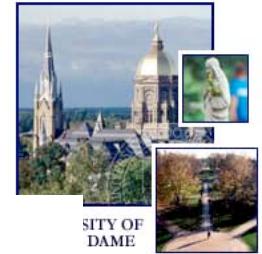
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π World Wide Web (WWW)

- No centralized control
- Exponential increase in diversity of information
- Websites arise and disappear seemingly at random (not necessarily true)
- Number of links pointing to page follow a power law
- A few pages are linked to many times and majority are seldom linked to



Other Emergent Structures

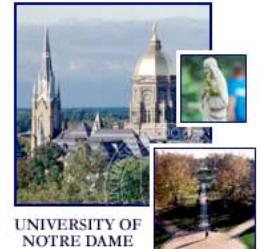


From
Animesh Mukherjee
CSE,IIT Kharagpur



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Effect of Genetics

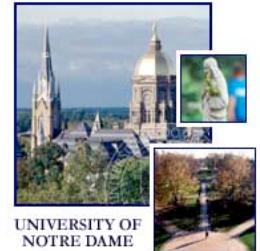


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- π Few traits caused by action of single gene
 - Most caused by many genes acting in concert
 - Many genes don't code for traits
 - Genes interact:
 - Turn one another on and off
 - Activation and inhibition control cellular development and activity
 - Generally not possible to find a gene "for" a certain trait
- π Most traits produced by networks of genes
 - Single gene may be part of >1 network
 - May cause traits to be linked, functionally or fortuitously
- π *Genome* of any organism can be regarded as a complex system.



The Question of Emergence



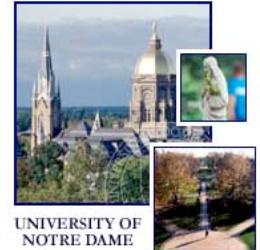
A Normal Given

Most people think of *social organization* in terms of a director, someone (or some thing) that is different from other participants in a group, who has in mind what the group is supposed to be doing, and who tells other participants what they should be doing to achieve the overall organization.

Problems:

- π Is it possible that there could be social organization without a director?
- π Could a group of individuals, all of whom are the same, achieve sophisticated social organization solely through their own interactions?
- π Could the behavior of such societies change over time even if the individuals didn't themselves change?

Types of Emergence

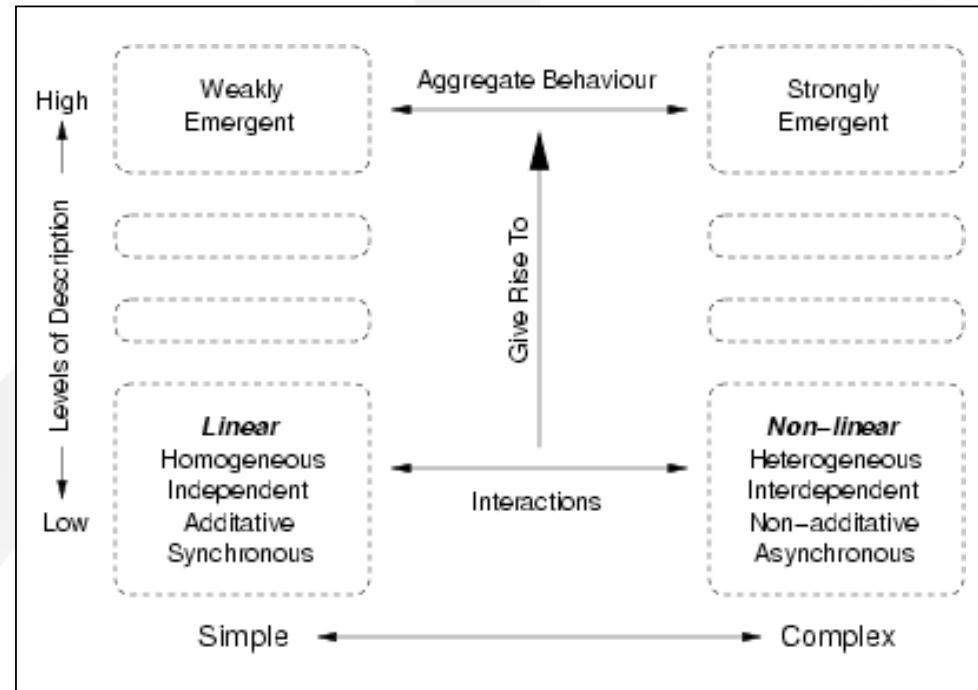


Weak Emergence

- The emergence results from a linear combination of the system components
- The emergent qualities are reducible to the individual components – Newtonian Physics

Strong Emergence

- The behavior of the Whole cannot be predicted from the parts since the combinations are non-linear in this case
- The emergent qualities are irreducible to the system components – systems theory of Physics

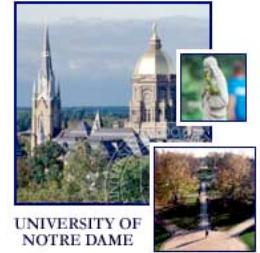


From Seth Bullock
Introduction to Complexity Science
Spring 2006



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Opposing Views



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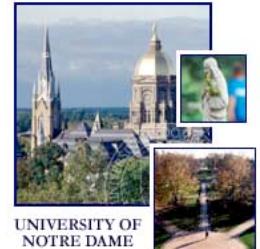
π Mark Bedau (1997) on strong emergence:

- "Although strong emergence is logically possible, it is uncomfortably like magic. How does an irreducible but supervenient downward causal power arise, since by definition it cannot be due to the aggregation of the micro-level potentialities? Such causal powers would be quite unlike anything within our scientific ken. This not only indicates how they will discomfort reasonable forms of materialism. Their mysteriousness will only heighten the traditional worry that emergence entails illegitimately getting something from nothing."

π Philip Anderson noted (Anderson 1972):

- "The ability to reduce everything to simple fundamental laws does not imply the ability to start from those laws and reconstruct the universe..The constructionist hypothesis breaks down when confronted with the twin difficulties of scale and complexity. At each level of complexity entirely new properties appear. Psychology is not applied biology, nor is biology applied chemistry. We can now see that the whole becomes not merely more, but very different from the sum of its parts."

Emergence: An Example



π Consider an automobile:

- Its requirement is that it can be driven from here to there.
- This is an emergent property in the sense that almost all parts of the automobile must operate correctly in order to achieve the desired result.
- BUT! The fulfillment of the requirement does not arise from any one part.

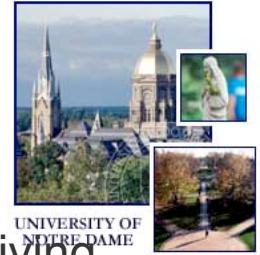


Exercise: Can this property be derived from a closed form mathematical expression of the automobile's components?



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Emergent Systems Theory



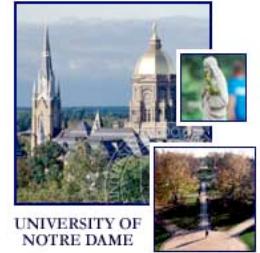
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- π 'emergent' refers to the state of being in continual process, never arriving, but always in transit
- π 'emergent' differs from 'emerging' because it gives rise to the possibility of a current state of being as a stage to a possible outcome always arising from its previous history and context.
- π Accepts that human systems are not deterministic; rather, they are products of constant social negotiation and consensus building
- π Sees human systems as in the process of moving towards structure and may exhibit temporal regularities of behavior, but they are never fixed or structured.
- π Accepts that there are emergent regularities but not unchanging relationships.
- π Holds that there are no points of theoretical stasis, only emergent regularities, and those regularities are always shifting and evolving.



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Emergent Systems: Core Ideas



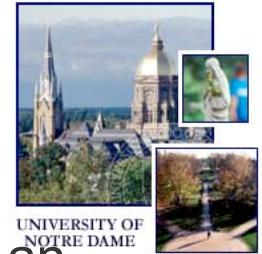
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- π Sophisticated behavior can result from simple interactions of simple things.
- π One can often usefully and relatively rigorously distinguish two general classes of emergent systems
 - Deterministic vs. Non-deterministic
- π There seem to be able four rigorously distinguish aspects of emergent systems
 - Agents, Environments, Observers/participants, Creator/architect/designer
- π Changes in behavior can occur due to changes in the environment without corresponding changes in an agent.
- π Both the agent(s) and the observer(s) can affect changes in the environment.



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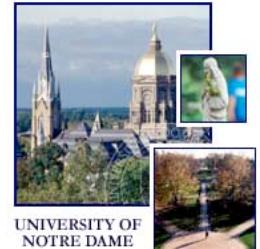
Emergent Systems: Core Ideas



- π A bidirectional relationship between an unchanging agent and an environment modifiable by the agent can produce behaviors that an observer may see as "purposive" even in a deterministic system.
- π Behaviors that appear "purposive" to an observer do not depend on any representation of the "purpose" within the agent.
- π Systems that exhibit "purposive" behavior need not depend on any conception of that "purpose" in the mind of a creator/architect/designer
- π Signs of "purpose", and even systems that exhibit what an observer would characterize as "purposive" behavior can come into existence simply because of indeterminate processes, i.e., need not involve minds at all.
- π That a world does things that are surprising to an observer does not establish whether it is deterministic or not.



Emergent Systems Theory

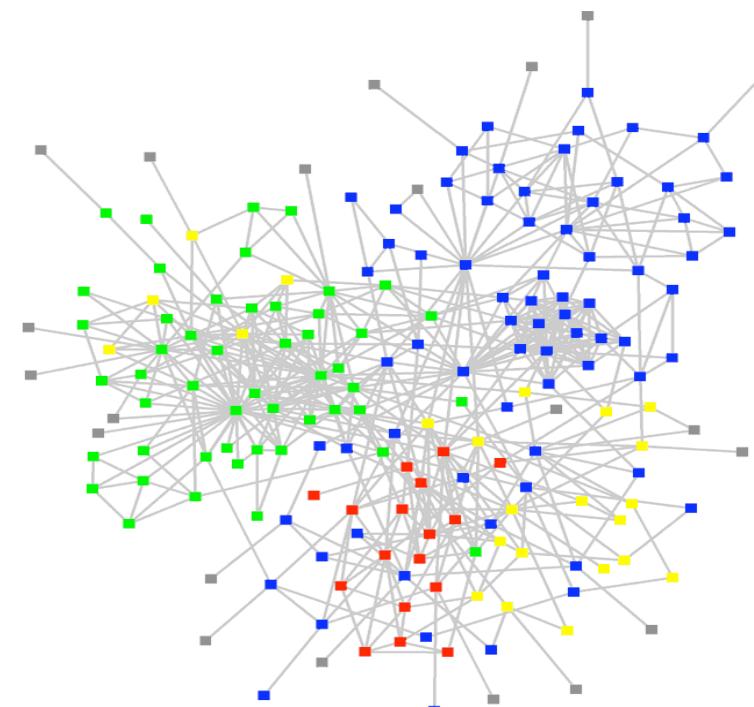


- π Views organizational/social behavior from a perspective that replaces fixed structures with one of continuous social re-construction.
- π Views process and 'becoming' as the default background and structure or regularities as the anomaly.
- π Views organizational emergence as not simply organizational change

Red, blue, or green:
departments

Yellow: consultants

Grey: external experts

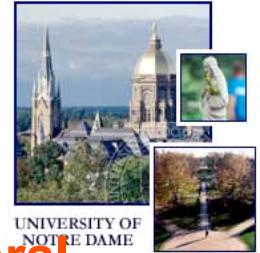


Source: www.orgnet.com



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Self-Organizing Systems (SOS)

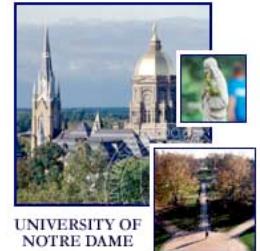


- π The spontaneous emergence of large-scale spatial, temporal, or spatiotemporal order in a system of locally interacting, relatively simple components.
- π Self-organization is a bottom-up process where complex organization emerges at multiple levels from the interaction of lower-level entities. The final product is the result of nonlinear interactions rather than planning and design, and is not known a priori.
- π Contrast this with the standard, top-down engineering design paradigm where planning precedes implementation, and the desired final system is known by design.



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SOS Properties



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π Consider the context of a software system:

Self-configuration:

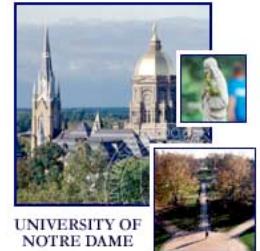
- An application is comprised of a set of abstract entities (a set of services with certain relationships)
- When started, an application collects certain components and assembles itself
- New components join dynamically: real ‘plug-n-play’

Self-optimization:

- All components must be optimal
- The system as a whole must be optimal
- These two can conflict
- There can be conflicting interests: multi-criteria optimization



SOS Properties



π Self-healing:

- System components must be self-healing (reliable, dependable, robust, etc)
- The system as a whole must be self-healing (tolerate failing components, incorrect state, etc)

π Self-protection:

- Protect oneself against intrusion and attacks

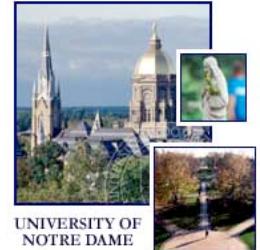
π Self-reflection

- Explicit knowledge representation: self-knowledge
 - Better in semantically rich and diverse environments
 - Plan and anticipate complex events (prediction)
- Ability to reason about and explain own behavior and state
 - More accessible administration interface
 - Higher level of trust from users



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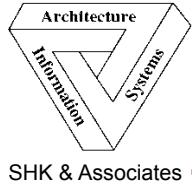
SOS Properties



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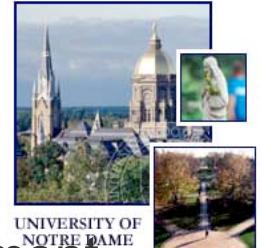
π Self-managing:

- Be able to maintain relationships with other elements
- Meet its obligations (agreements, policies)
- Be able to identify on its own what services it needs to fulfill its obligations
- Policies:
 - Action policies
 - If then rules
 - Goal policies
 - Requires self-model, planning, conceptual knowledge representation
 - Utility function policies
 - Numerical characterization of state
 - Needs methods to carry out actions to optimize utility (difficult)



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Adaptive Software - I



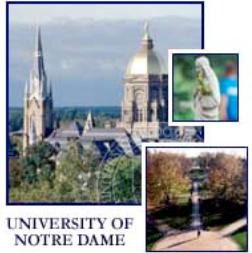
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- π Software that can adapt dynamically to changes in its environment and non-functional requirements.
- π Increased interest in adaptive systems due to the following:
 - Ubiquitous Computing – dissolving traditional boundaries for how, when, and where humans and computers interact
 - Growing demand for autonomic computing
- π Two Approaches:
 - **Parameter Adaptation** – modify program variables that determine behavior
 - Limitation: Cannot adopt new strategies
 - **Compositional Adaptation** – software to modifies its structure and behavior dynamically in response to changes in its executing environment
 - Enables dynamic recomposition of software during execution



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Adaptive Software - II



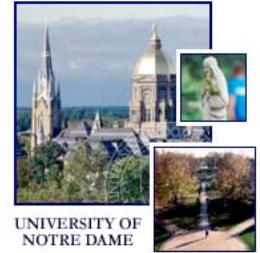
Some Current Composition Techniques:

Table 2. Software recomposition techniques.

Technique	Description	Examples
Function pointers	Application execution path is dynamically redirected through modification of function pointers.	Vtables in COM, delegates and events in .NET, callback functions in Corba
Wrappers	Objects are subclassed or encapsulated by other objects (wrappers), enabling the wrapper to control method execution.	ACE, R-Java, PCL, QuO, TRAP/J
Proxies	Surrogates (proxies) are used in place of objects, enabling the surrogate to redirect method calls to different object implementations.	ACT, AspectIX
Strategy pattern	Each algorithm implementation is encapsulated, enabling transparent replacement of one implementation with another.	DynamicTAO and UIC
Virtual component pattern	Component placeholders (virtual components) are inserted into the object graph and replaced as needed during program execution.	ACE and TAO
Metaobject protocol	Mechanisms supporting intercession and introspection enable modification of program behavior.	Open Java, Kava, TRAP/J, Open ORB, Open COM, Iguana/J
Aspect weaving	Code fragments (aspects) that implement a crosscutting concern are woven into an application dynamically.	AspectJ, Composition Filters, TRAP/J, AspectIX, Iguana/J, Prose
Middleware interception	Method calls and responses passing through a middleware layer are intercepted and redirected.	ACT, IRL, Prose
Integrated middleware	An application makes explicit calls to adaptive services provided by a middleware layer.	Adaptive Java, Orbix, Orbix/E, ORBacus, BBS, CIAO, Iguana/J, Ensemble

Source: Composing Adaptive Software by McKinley, Sadjadi, Kasten and Cheng

Adaptive Software: A Model

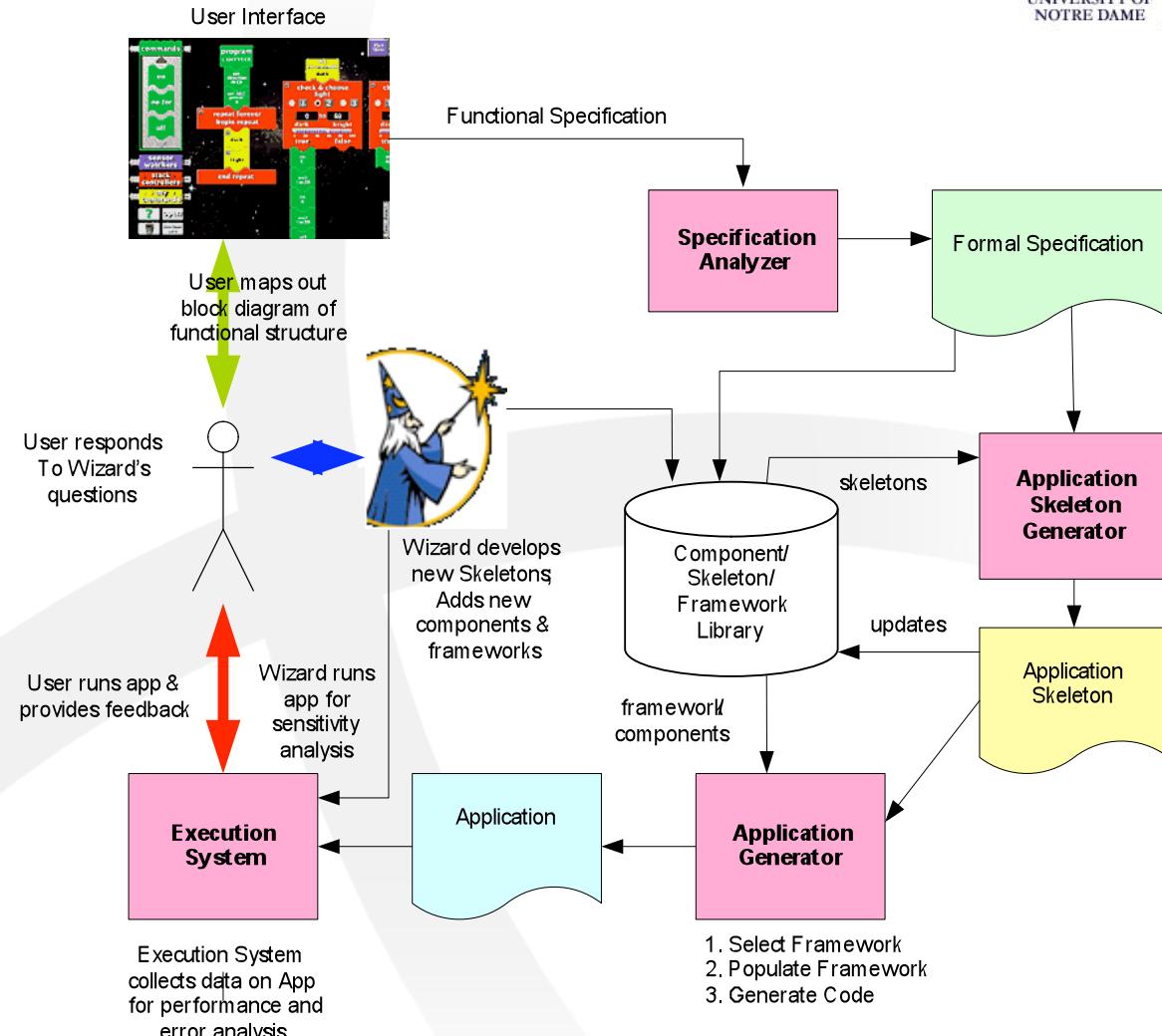


Motivation:

- A programmer costs ~ \$1/minute, produces ~8-16 lines of usable code per day: \$30 - \$60 per line of code (~ \$120K per year for ~2000-4000 lines of usable code/year)

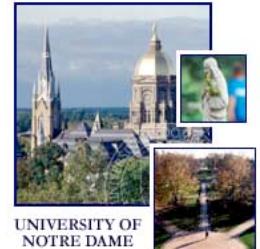
- Good debugged applications may still take days or weeks.

- With reusable components, automatic generation of glue code, data transformers, and instrumentation, we produce new applications in hours rather than days or weeks





The Challenge!



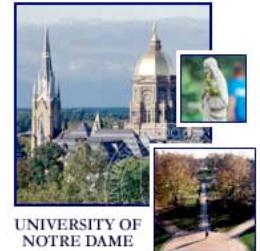
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- π A new paradigm for systems development:
 - Provide the basic elements/components needed
 - Let the components interact among themselves and with the environment to organize through an iterative process of **creative exploration** and **selective destruction**
 - Need metrics for assessing the goodness of design
- π In complex environments that change all the time, we cannot anticipate all situations:
 - We cannot pre-design a system that is always guaranteed to work
- π Not necessarily a Trial and Error Approach
- π Not for all types of systems
 - I wouldn't want the payroll system designed like this!!



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Emergence: References



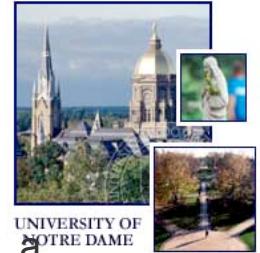
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- π Johnson, S. 2001. *Emergence: The Connected Lives of Ants, Brains, Cities, and Software*, Touchstone, New York
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- π [Laughlin, Robert](#). 2005. [A Different Universe: Reinventing Physics from the Bottom Down](#), Basic Books, [ISBN 0-465-03828-X](#)
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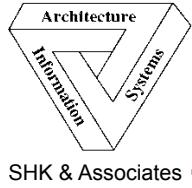
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References

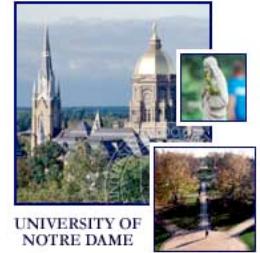


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- π Johnson, S. 2001. Emergence: The Connected Lives of Ants, Brains, Cities, and Software, Touchstone Press
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<http://llk.media.mit.edu/projects/emergence/>
- π Sawyer, R.K. 2003. "Artificial Societies: Multiagent Systems and the Micro-Macro Link in Sociological Theory", *Sociological Methods and Research*, 31(3):325-363

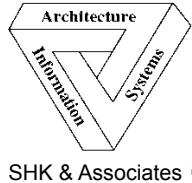


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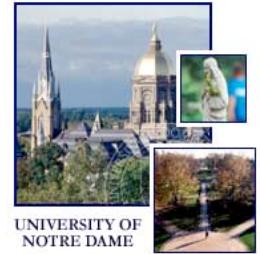
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Complex Adaptive Systems Tools & Techniques



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Techniques for CASs/CESs



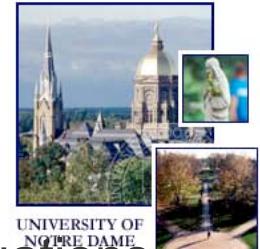
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Dynamical Systems	Differential or difference equations of low-dimensionality representing competing adversaries (including the <i>systems dynamics</i> approach).
Game Theoretic Models	Based on the application of 2-person and n-person games to social situations with strategic interdependence; computer simulations.
Control-theoretic Models	Applying linear, non-linear, and optimal control theory principles to Interactions among social and political entities.
Evolutionary Computation	Applying a variety of evolutionary methods (e.g., genetic algorithms) to social simulation models.
State Transition Systems	Based on modeling interactions among social and political entities as transitions between known states (including cellular automata/Petri nets).
Social Network Analysis	Phenomena can be understood as collections of interacting components, modeled as graphs, with emergent properties characterized by SNA.
Agent-Based Simulations	Applications of large-scale agent-based systems to simulate, agents, human and social dynamics in complex environments.
Rule-Based Systems Multi-Agent Systems	Applications of complex rule systems and other AI techniques to simulate reasoning agents or humans in complex environments.



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Dynamical Systems

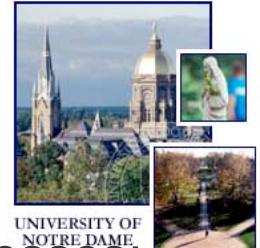


- π *Dynamical systems* are sets of time-dependent differential equations used to model physical or social phenomena:
 - Whose state (or instantaneous description) changes over time
 - Variability can be described causally
 - Important causal influences can be contained within a closed system of feedback loops
- π Three broad categories:
 - Generative: the objective is to predict future states of the system from observations of the past and present states of the system
 - Diagnostic: the objective is to infer what possible past states of the system might have led to the present state of the system (or observations leading up to the present state)
 - Explanatory: the objective is to provide a theory for the physical or social phenomena



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Dynamical Systems

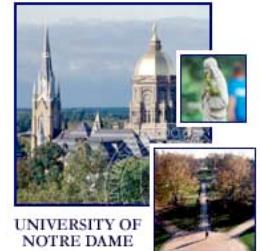


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- π Dynamic systems tend to exhibit two disparate kinematic processes:
 - The emergence of new structures, paths, and processes from past states
 - The emergence of repetitive cycles of phenomena (for better or worse)
- π Dynamical systems are good for representing, explaining, and modeling change over time
 - The system evolves in time according to a set of fixes rules
 - Present conditions determine the future (Laplacian assumption)
 - The rules are usually nonlinear
 - There are many (many) interacting variables



Dynamical Systems Theory

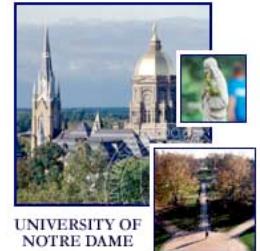


- π States changing over time within a state space
- π States are characterized by a fixed set of variables; e.g., x_1, x_2, x_3, x_4
- π Specific values assigned to these variables define a specific state; for example, $x_1 \leftarrow 0.06, x_2 \leftarrow 1.84, x_3 \leftarrow 3.36, x_4 \leftarrow -0.27$
- π Properties:
 - Step Property: State at $t+1$ derives from state t by some formula



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Example: Conflict Dynamics



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- π Richardson's (1960) 2-country interactive theory
- π Let X and Y denote the levels of arms of countries A and B, respectively
- π Assumption 1 (Fear): Each country increased its level of armaments in proportion to the other's level: $dX/dt \propto Y$ and $dY/dt \propto X$.
- π Assumption 2 (Cost): Each country is restrained by the existing level of armaments: $dX/dt \propto -X$ and $dY/dt \propto -Y$.
- π Assumption 3 (Insurance): Each country will always increase its armaments by some fixed amount, because of distrust.
- π Then:

$$dX/dt = aY - bX + g$$

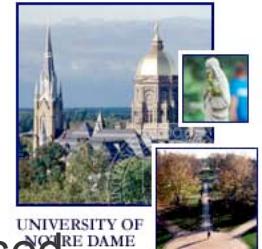
$$dY/dt = a'X - b'Y + h$$

where g and h are the hostility coefficients.



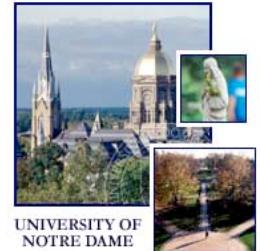
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Dynamical Systems Challenges



- π Knowing how to specify the dependencies $f(x_1, x_2, x_3, \dots, x_n)$ in closed form
 - Many times we only know qualitative rules
- π Non-stationarity of coefficients
 - E.g., sensitivities can change
- π Feed-back and feed-forward: control and anticipation
 - People and groups think; planets do not
 - Free will
- π Structural instability
 - Functional relations can change over time (diachronics)
 - Dependencies can form and dissolve
- π Created for celestial mechanics, not human and social dynamics
 - Most valid as theoretical models to understand a limited range of highly aggregate qualitative behavior (e.g., demography, macroeconomics)
- π Sensitive Dependence on initial conditions
 - Measurement error, Quantum effects, etc.

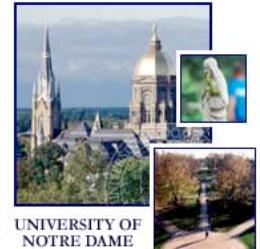
Cellular Automata



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- π Originated with E. F. Codd and John von Neumann in 1950s
- π Popularized by John Conway's Life Game, *Scientific American*, 1970
- π Basis for Stephen Wolfram's book, *A New Kind of Science*. See M. Mitchell's (2002) review.
- π Basic Structure:
 - A collection of fixed cells arrayed in a grid
 - Each cell is ON or OFF
 - A set of rules which are uniformly applied to the contents of each cell at each iteration of the automaton.
 - Initial configuration Neighborhood pattern for the next generation
- π What Happens?
 - The structure of the cellular automaton evolves through a number of time steps based on the application of the rules and the contents of the cells and their neighbors.

Conway's Game of Life - I

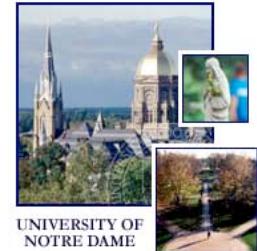


- π An early example of 'emergent complexity' (1970)
 - Based on the rules chosen, one gets different objects with interesting properties
- π Implemented as a 2-dimensional cellular automata
- π Basic Ideas:
 - Life is played on a grid of square cells
 - A cell can be *live* or *dead*
 - A live cell is shown by putting a marker on its square
 - A dead cell is shown by leaving the square empty
 - Each cell in the grid has a neighborhood consisting of the eight cells in every direction including diagonals.
- π Rules:
 - An agent stays alive if 2 or 3 neighbors are alive, otherwise it dies.
 - New agent is born if exactly 3 neighbors are alive.

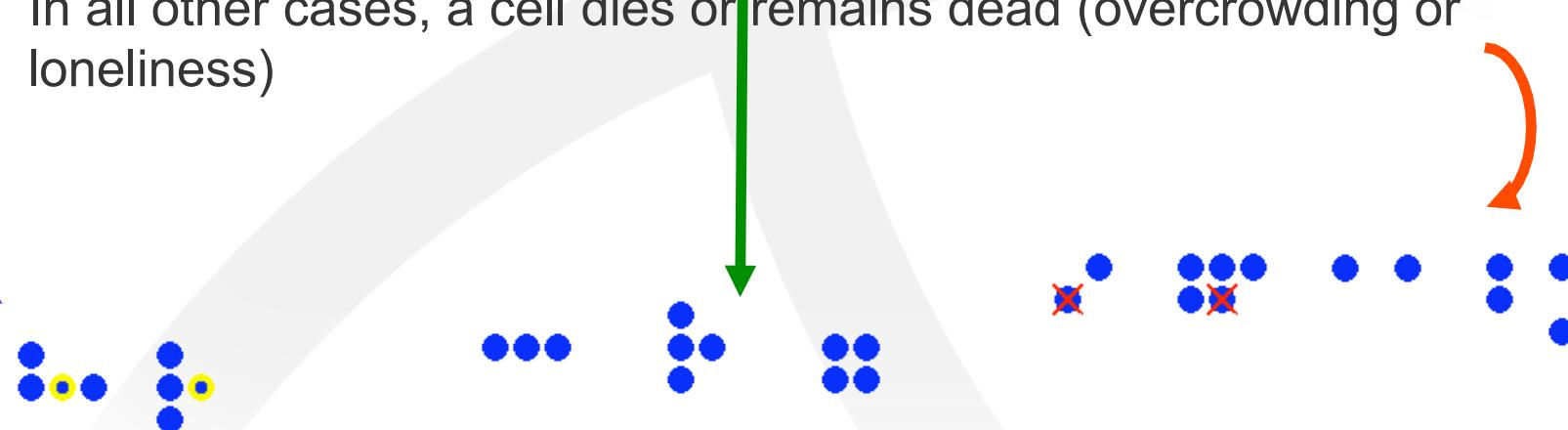


John Conway

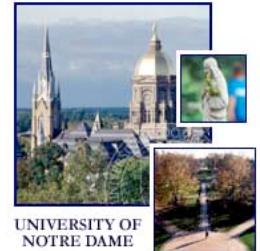
Conway's Game of Life - II



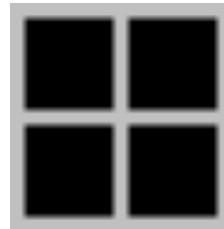
- π To apply one step of the rules, we count the number of live neighbors for each cell.
 - The number of live neighbors is always based on the cells **before** the rule was applied. In other words, we must first find all of the cells that change before changing any of them.
- π A dead cell with exactly three live neighbors becomes a live cell (birth)
- π A live cell with two or three live neighbors stays alive (survival)
- π In all other cases, a cell dies or remains dead (overcrowding or loneliness)



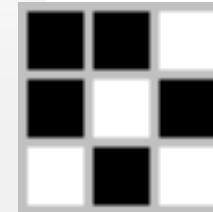
Emergent Patterns



π Static Patterns

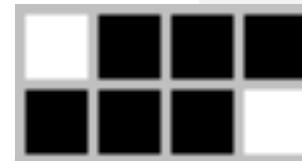


Block



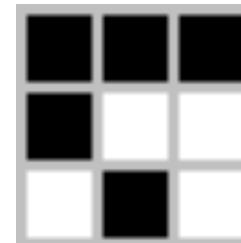
Boat

π Oscillator – Periodically repeating patterns



Toad

π Spaceships – Patterns that translate over the automaton space

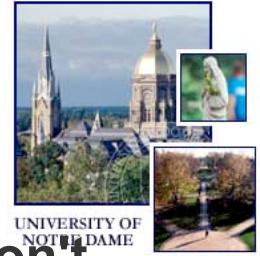


Glider



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Why Is *Life* Interesting?



π Game of Life lets us experiment with systems where we don't know all the rules

- Study simple systems to learn basic rules
- Build on this knowledge to construct more complex systems
- The rules are all that is needed to discover 'new' phenomena within the Life universe
- Initial boundary conditions (e.g., the starting pattern(s)) lead to interesting phenomena, just as in the real world

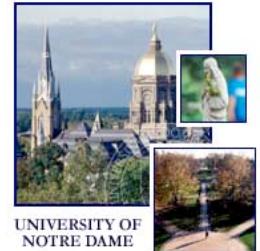
π Key Challenge!

- At what point can systems such as Life be presumed to model the real world?
In complexity? In fidelity?
- Question: Can we adequately explain complex systems with sets of simple rules?

π It's Fun To Play With!! <http://cs.gmu.edu/~eclab/projects/mason/>



Applying CAs to Social Sciences



π T. Schelling's (1971) Segregation Model

- Placed dimes and pennies on a chess board and moved them around according to various rules
- Interpreted board as a city w/ each square representing a house or a lot
- Pennies and dimes represented agents, e.g. two races
- Neighborhood of an agent was the squares adjacent to the square in which the agent resided
- Rules determined whether an agent was happy in its current location
- If unhappy it could move to another location or exit the board entirely.

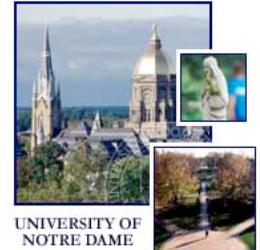
π Results:

- The board became segregated even if the agent's "happiness Rules" did *not* favored segregation
- The board became segregated if an initially integrated board had happiness rules that expressed a mild preference for neighbors of their own type.



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Cellular Automata



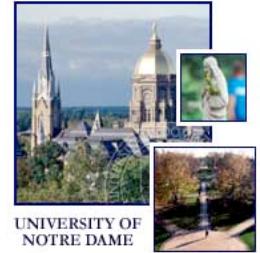
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π Variations:

- # Dimensions > 2:
 - Do other properties emerge as the number of dimensions increases?
- Different neighborhood rules:
 - Von Neumann : only North/South/East/West neighbors are considered
 - Extended Moore: consider neighbors one beyond immediate
- # States > 2
- Different birth/death/survival rules
- Bounded vs. Unbounded Spaces



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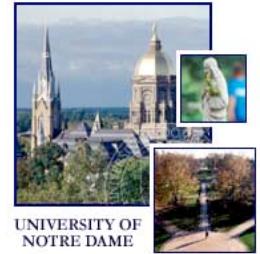
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Agent-Based Simulation



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Agent-based Simulation: Toolkits



- MASON
- Repast Symphony
- Ascape
- Swarm
- NetLogo
- StarLogo
- Breve
- ... and 50+ more

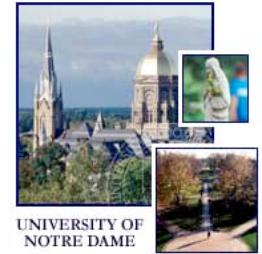


StarLogo TNG

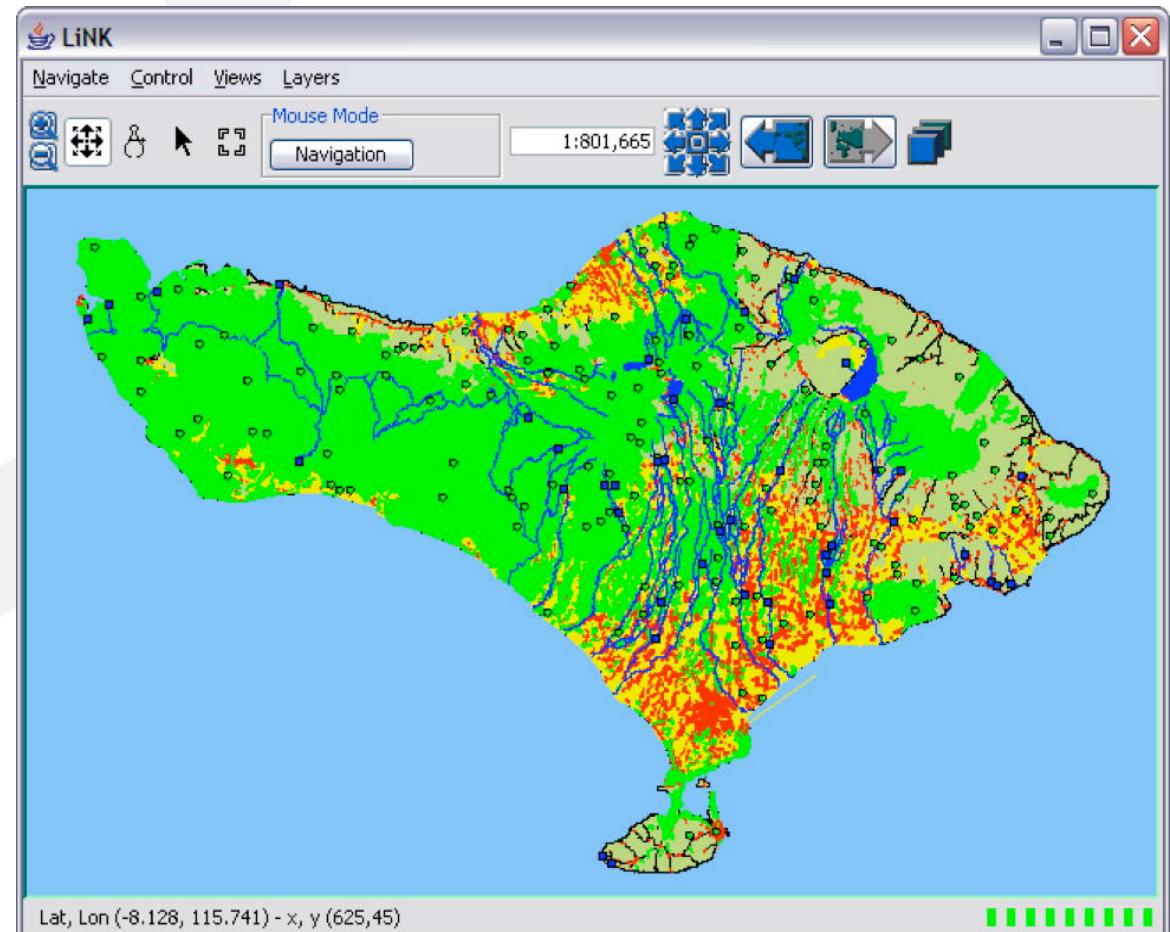
http://www.swarm.org/wiki/Tools_for_Agent-Based_Modelling
http://en.wikipedia.org/wiki/ABM_Software_Comparison



Agent-based Simulation with GIS



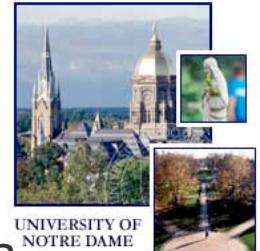
- Spatially aware agents
- Real geospatial constraints
- Multiple layers
- Face validation easier
- Helpful for discovery





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The MASON Toolkit



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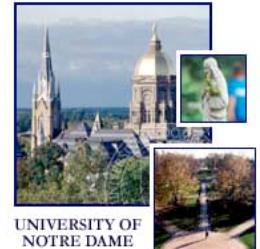
- π MASON (Multi-Agent Simulator of Networks and Neighborhoods) is a
 - general-purpose,
 - single-process,
 - discrete-event simulation library for building diverse multiagent models across
 - the social and computational sciences (AI, robotics),
 - ranging from 3D continuous models,
 - to social complexity networks,
 - to discretized foraging algorithms based on evolutionary computation (EC)

- π Design principles:
 - *intersection* (not union) of needs
 - “additive” approach
 - divorced visualization
 - Checkpointing
 - EC

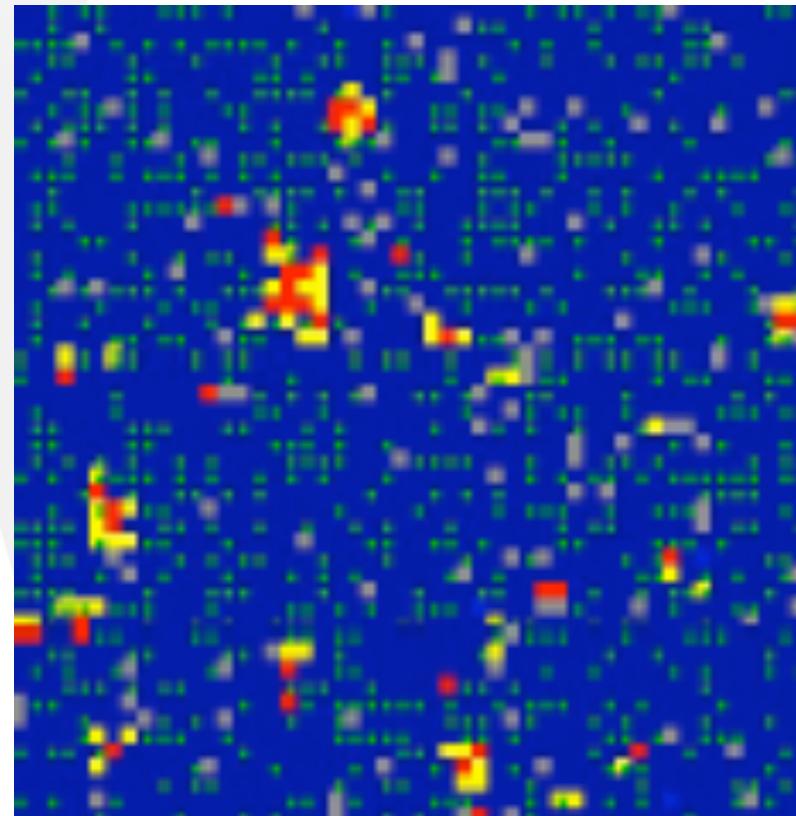


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MASON Application Models

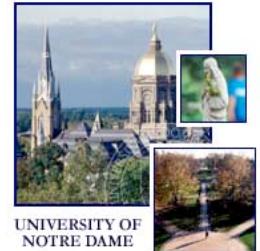


- π HeatBugs (MT)
 - Classic, 3D, HexaBugs
- π Conway's Life
- π Schelling's segregation
- π Agent foraging
 - Static & moving food
- π Virals
 - Anthrax, cybersecurity
- π Wetlands
 - Agent 05, CollInt IV



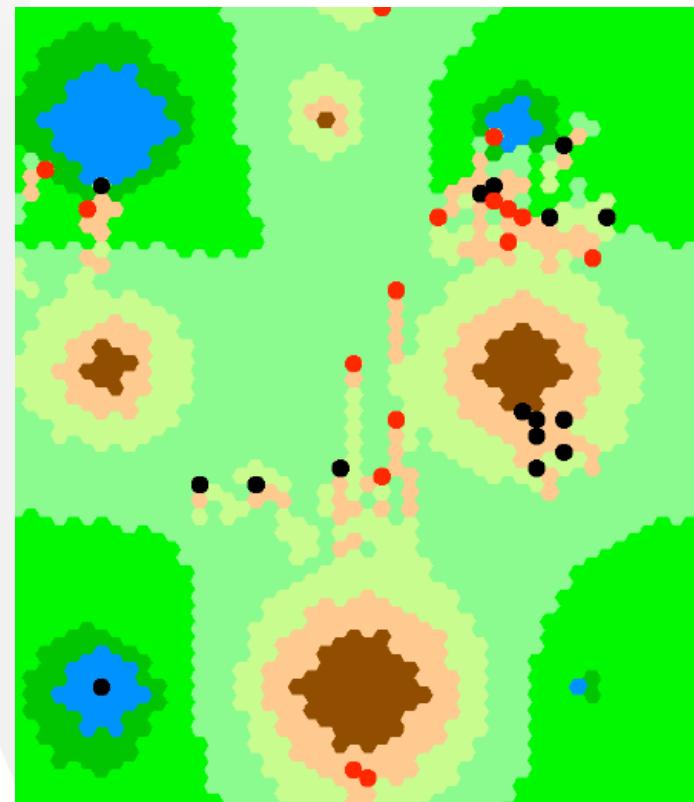


MASON “Wetlands” Model



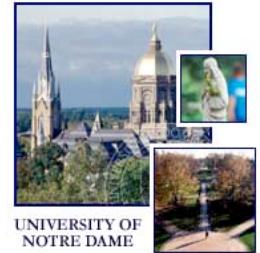
π STATICS (“ontology”):

- Artificial world classes
 - Group-level social agents
 - Physical environment
- Physical environment *layers*
 - Landscape of hex cells
 - Food distribution (green)
 - Shelter sites (brown)
 - Weather (rain)
 - Real world: simple ecotope
- Heterogeneous social agents
 - Groups, not individuals
 - Two cultures: Atis (red) and Etis (black) each *with same social memory structure.*





MASON “Wetlands”

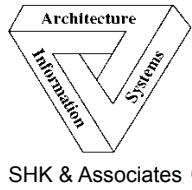


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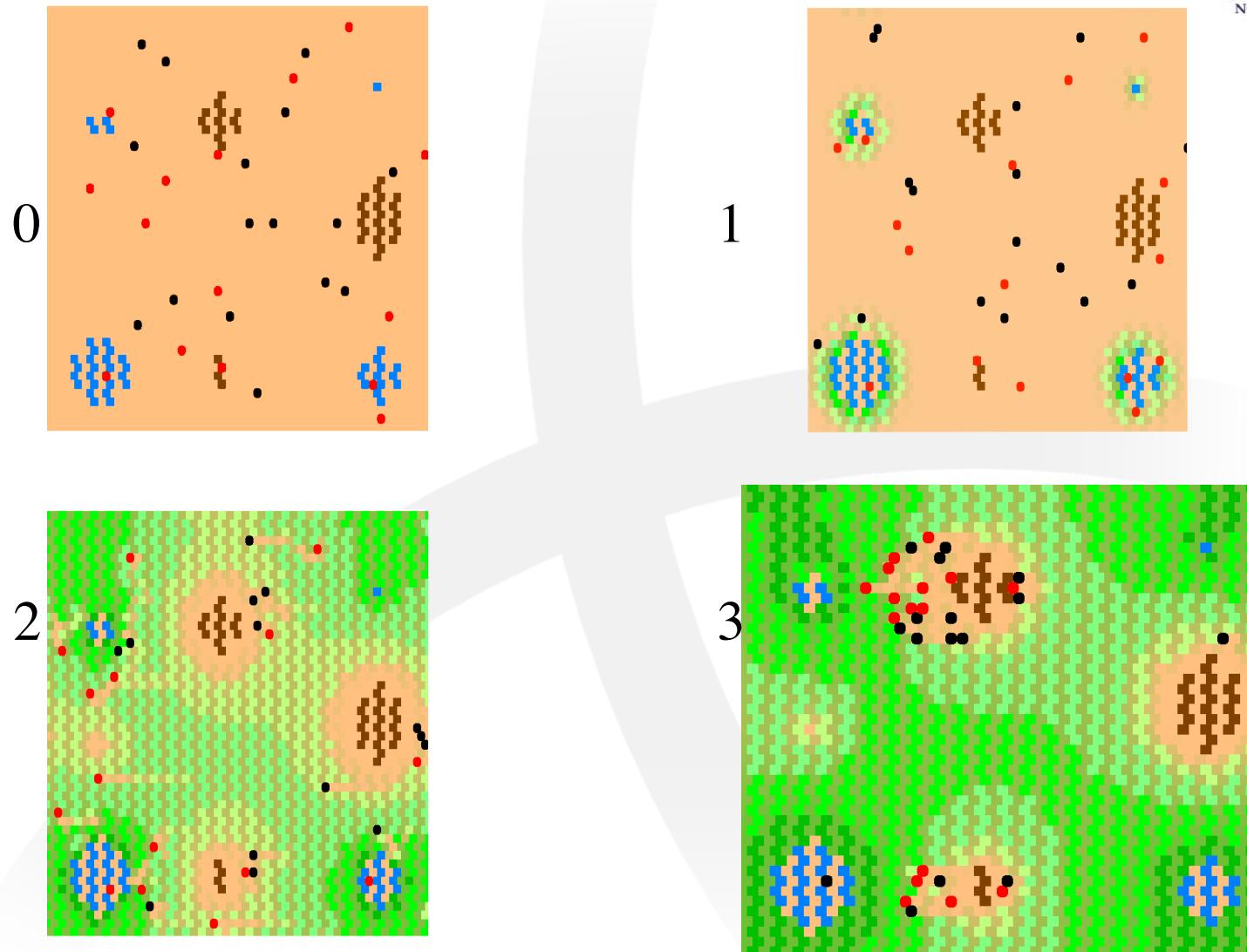
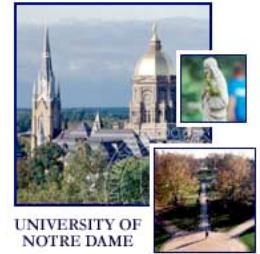
DYNAMICS:

1. Rain (blue) occurs constantly, causing food (green) to grow.
2. Agents move seeking food, which consumes energy and makes them wet.
3. IF an agent gets too wet it will seek shelter (brown sites) until dry enough to go out to eat again again.
4. Agents share information (or “mind-read”?) on food and shelter location *only* with agents of same culture that they encounter nearby.
5. There is *no* rule to behave collectively.



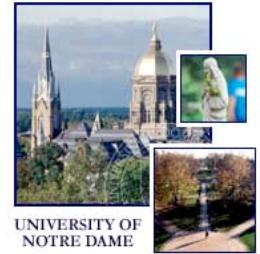
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Observed Wetlands regimes

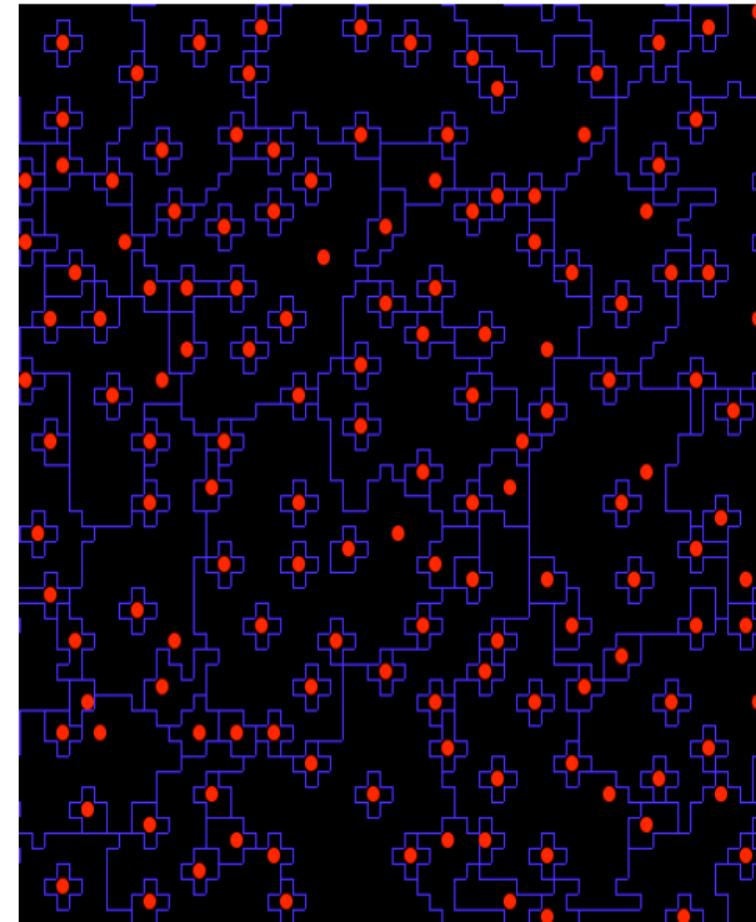




Examples of MASON models (open-source)



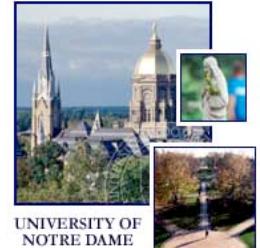
InterHex.MASON
Model of an international system with incomplete knowledge and (eventually) EC





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*Modeling tools are only as good as what they can actually model
(Kline's thesis): What ABMs Simulators (Swarm, Ascape, RePast,
MASON et al.) can model:*

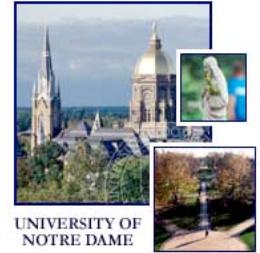


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- π Climate
- π 2D and 3D environments and neighborhoods
- π Decision-making
- π Memory
- π Deception
- π Leadership
- π Strategic choice
- π Trade
- π Accumulation of wealth
- π Networks
- π Flocking
- π Migration
- π Foraging
- π Agriculture
- π Land-use patterns
- π Warfare
- π International war
- π Peacekeeping
- π Civil violence
- π Colonization
- π Urbanization
- π Alliance dynamics
- π Collective action



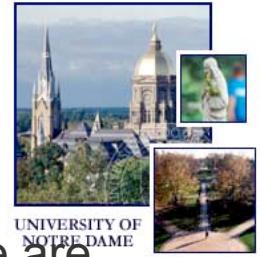
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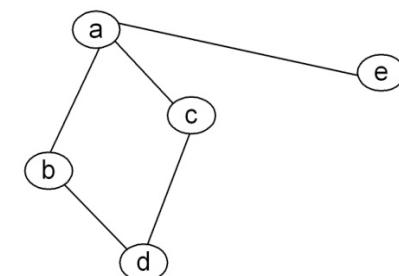
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Social Network Analysis

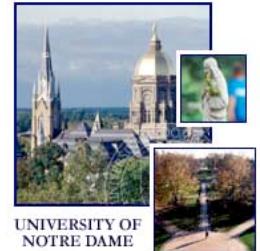
Graph Theory Primer - I



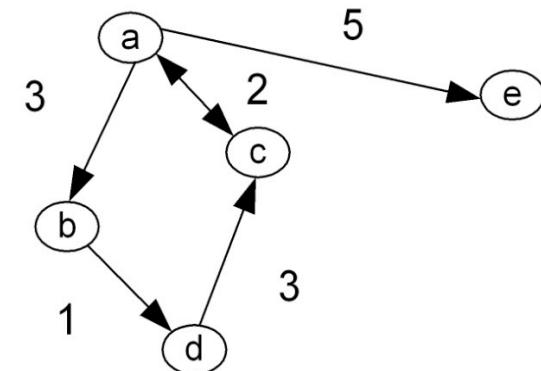
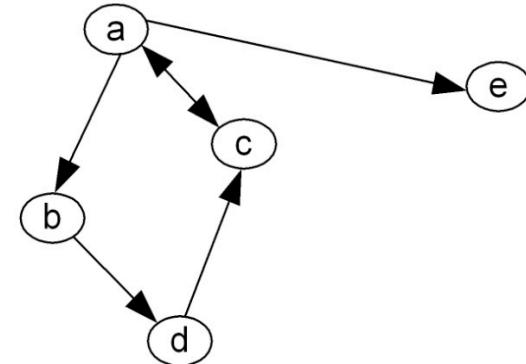
- π Social network data consists of binary social relations, of which there are many kinds (role-based, affective, cognitive, flows, etc.)
 - Mathematically, social networks can be represented as graphs or matrices.
- π A *graph* is defined as a set of nodes and a set of lines that connect the nodes, written mathematically as $G=(V,E)$ or $G(V,E)$.
- π The *nodes* in a graph represent persons (or animals, organizations, cities, countries, etc) and the *edges* (lines) represent relationships among them.
 - The line between persons a and b is represented mathematically like this: (a,b) .
 - The graph here contains these edges: (a,b) , (a,e) , (b,d) , (a,c) , and (d,c) .
 - A *subgraph* of a graph is a subset of its points together with all the lines connecting members of the subset. ($\text{subgraph} = \{a, b, c, d\}$)
- π The degree of a point is defined as the number of lines incident upon that node.
 $\text{degree}(a) = 3$

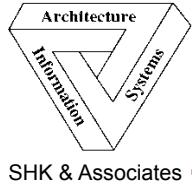


Graph Theory Primer - II



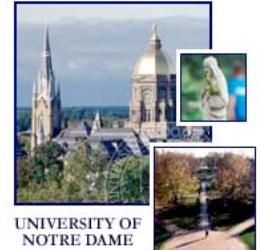
- π If a node has degree 0 it is called an *isolate*.
- π In a *directed graph*, the edges have direction (indicated by arrow heads)
- π If a line connects two points, they are said to be "*adjacent*".
- π The two points connected by a line are called *endpoints*.
 - An edge that originates or terminates at a given point is "*incident*" upon that point.
 - Two edges that share a point are also said to be *incident*.
- π A *weighted graph* has values assigned to the edges.





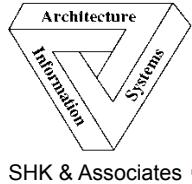
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Graph Theory Primer - III



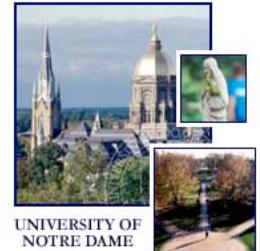
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- π In a directed graph, a point has both indegree and outdegree:
 - The *outdegree* is the number of arcs from that point to other points.
 - The *indegree* is the number of arcs coming in to the point from other points.
- π A *path* is an alternating sequence of points and lines, beginning at a point and ending at a point, and which does not visit any point more than once.
 - Two paths are point-disjoint if they don't share any nodes.
 - Two paths are edge-disjoint if they don't share any edges.
 - A walk is a path with no restriction on the number of times a point can be visited.
 - A cycle is a path except that it starts and ends at the same point.
 - The *length of a path* is defined as the number of edges in it.
 - The shortest path between two points is called a *geodesic*.



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SNA: Centrality

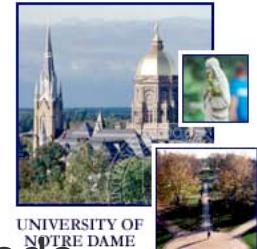


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π Centrality:

- A stratification measure
- How to measure "power"
- π Does success depend on local or distal connections?
- π Does success depend on the power/centrality of other actors/vertices to which a focal vertex is connected?
- π Do resources “flow through” intermediary nodes, so that indirect relationships become proxies for direct ones?
- π Or is centrality more in the way of an indicator of exchange opportunities/bargaining power?
- π What are the “rules of the game” as regards the activation of multiple relationships?

SNA: Centrality

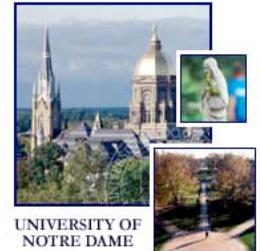


- π *Degree Centrality*: number of distinct relationships or links a node has
 - $C_D(i) = \sum x_{ij}; j = 1, N$ and $i \neq j$
 - $\underline{C_D}(i) = C_D(i)/(N-1)$ normalized value
 - Differentiate by "in" and "out" connections based on which way power & influence flow
- π *Betweenness Centrality*: measures control or broker ability of a node
 - Assume this "process" is efficient because it occurs along geodesic paths
 - Maximum "betweenness" is for an intermediary node in a star network
- π *Closeness*: who can reach others via few intermediaries are relatively independent/autonomous of others
 - Intermediaries serve as attenuators and filters



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SNA: Centrality



π "Eigenvector" centrality:

- There exist multiple central nodes in the network
- The centrality of a vertex depends on having strong ties to other central vertices
- "Status" rises through strong affiliations with high-status others
- Compute: $e_i = f(\sum r_{ij}e_j; j = 1, N)$ where e_i is the eigenvector centrality measure and r_{ij} is the strength of the relationship between i and j (sometimes thought of as j 's dependence on i)

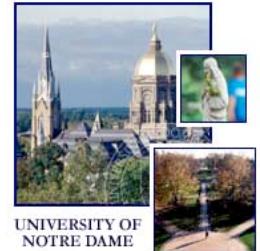
π What else can we measure?

- Lots of different measures
- Weighted, directional graphs to measure "flow of influence"
- Borgatti/Everett partition networks into "core" and "periphery" graphs connected by key nodes



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SNA Websites



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- π International Network for Social Network Analysis

<http://www.insna.org/>

- π Valdis Krebs, <http://www.orgnet.com/>

- π Analytic technologies, <http://www.analytictech.com/>

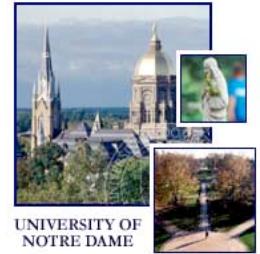
- π Networks/Pajek,

<http://vlado.fmf.uni-lj.si/pub/networks/pajek/default.htm>



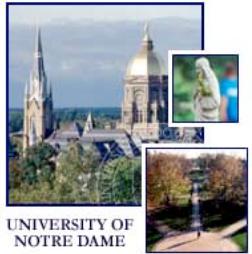
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Recommended Readings



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1. Gillespie, John V., and Dina A. Zinnes. 1975. Progressions in mathematical models of international conflict. *Synthese* 31 (2):289-321.
2. Schrot, Philip A. 1976. Richardson's model as a Markov process. In *Mathematical Models in International Relations*, edited by D. A. Zinnes and J. V. Gillespie. New York: Praeger.
3. Zinnes, Dina A., and Robert G. Muncaster. 1984. The dynamic of hostile activity and the prediction of war. *Journal of Conflict Resolution* 28 (2): 187-229.
4. Coleman, James S. 1964. *Introduction to Mathematical Sociology*. New York: The Free Press of Glencoe.
5. Boynton, G. Robert. 1980. *Mathematical Thinking About Politics*. New York: Longman.
6. Cortes, Fernando, Adam Przeworski, and John Sprauge. 1974. *Systems Analysis for Social Scientists*. New York: John Wiley and Sons.
7. <http://www.math.com/students/wonders/life/life.html>



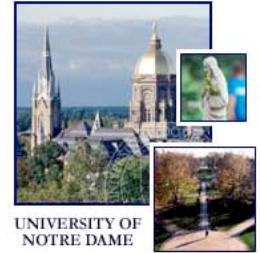
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CAS Examples & Applications

Human-Primate Disease Transmission
Disaster Modeling & Management
Social Science Research



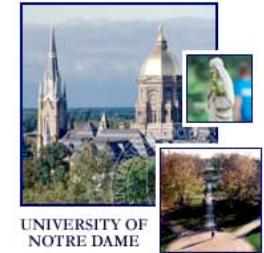
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Human-Primate Interaction Disease Transmission

A Complex Adaptive System



π Macaques

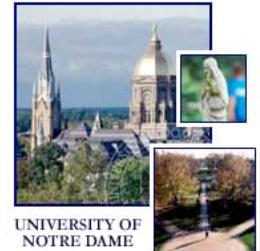
- Coexisted with people at temples across the island for at least 2000 years
- Populations are female philopatric; males migrate from natal populations at age 7
- Changing land use patterns have resulted in increased macaque-human interactions

π Disease Transmission

- Primates are implicated as host and reservoir in several disease emergences
- Increases in human to non-human primate interaction can lead to potential increases in bi-directional pathogen transmission
- Long term human-macaque interface could become potential site of global disease emergence

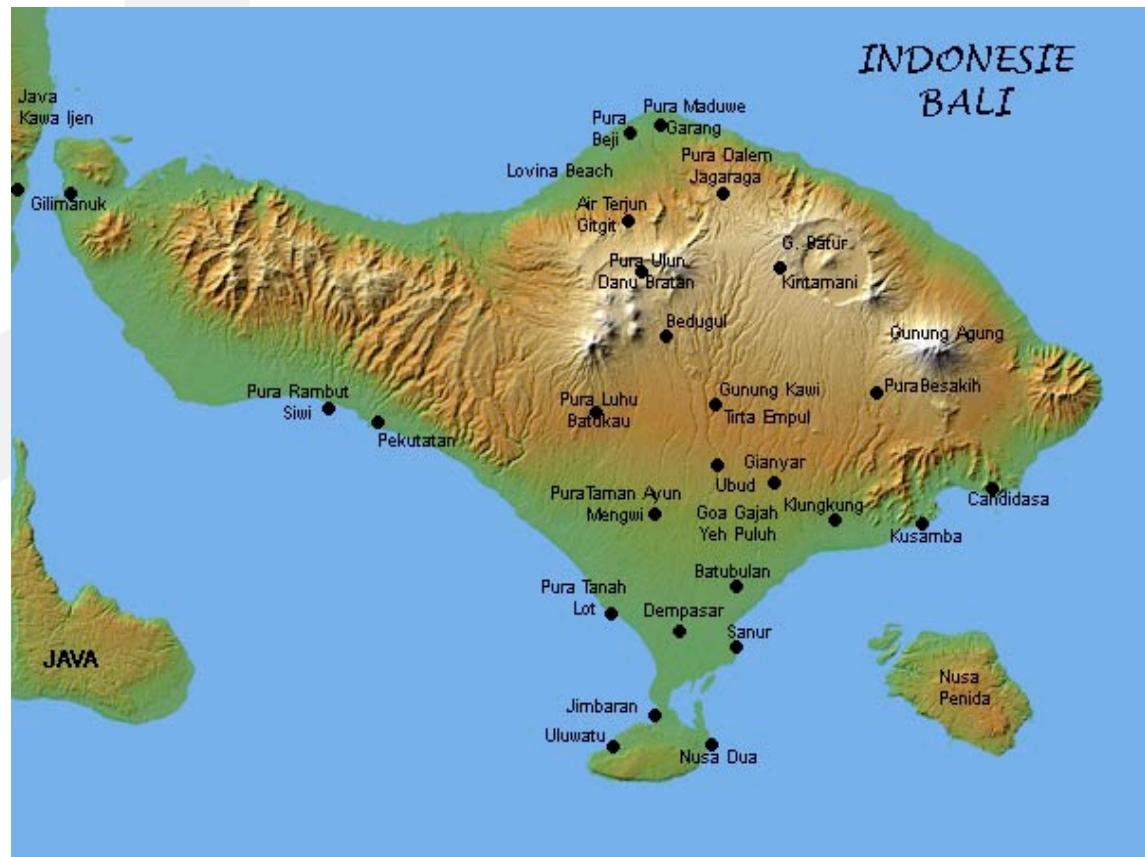


Background

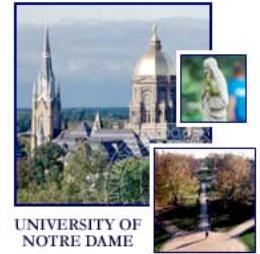


π Bali

- Small Indonesian island (~130km x 80km)
- Roughly 3 million people and 10,000 macaques
- 42 Temple Sites
 - Majority of macaque population (and all females) reside here
 - Lots of macaque-primate interaction at these sites

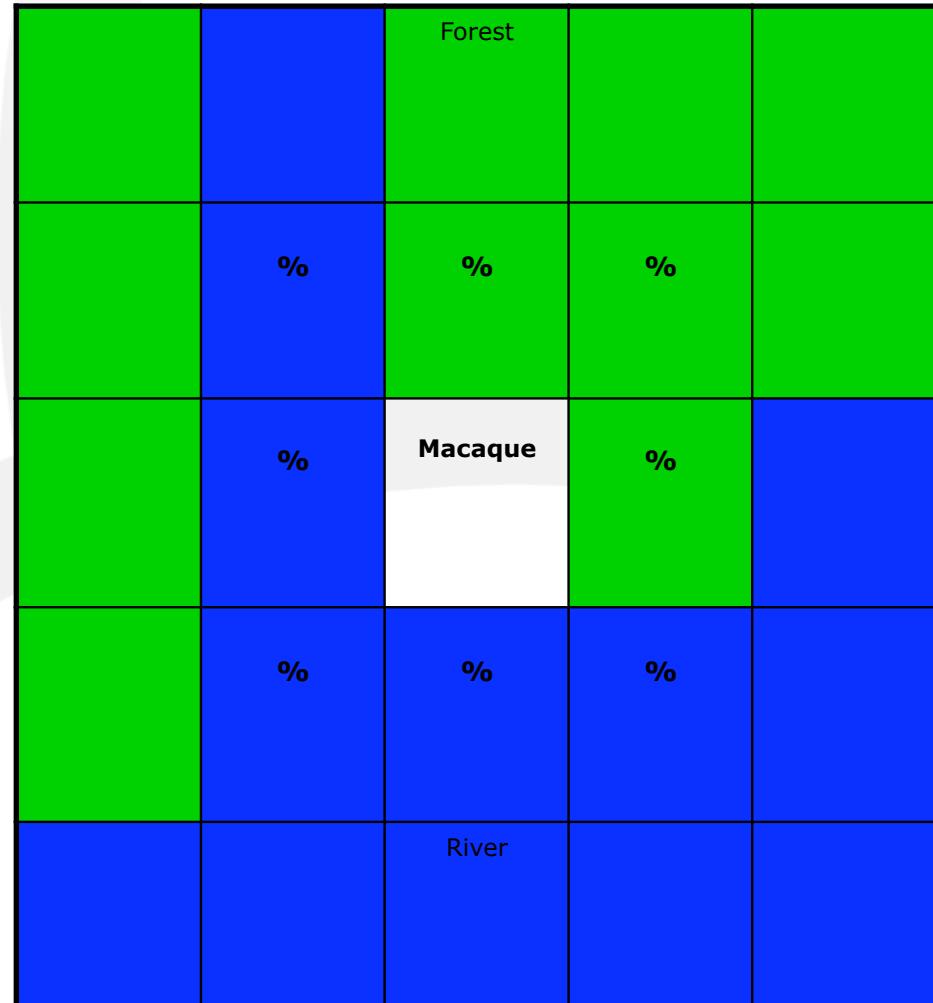


Model Background



π Movement

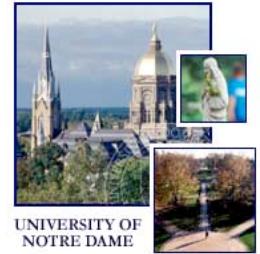
- Stochastic
- Can be based upon arbitrary number of cells outward
- Space is a cellular grid
- Grid cells determined by GIS layers





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Model Details



Agents

- Macaques with studied behavior and habitat probabilities

Environment

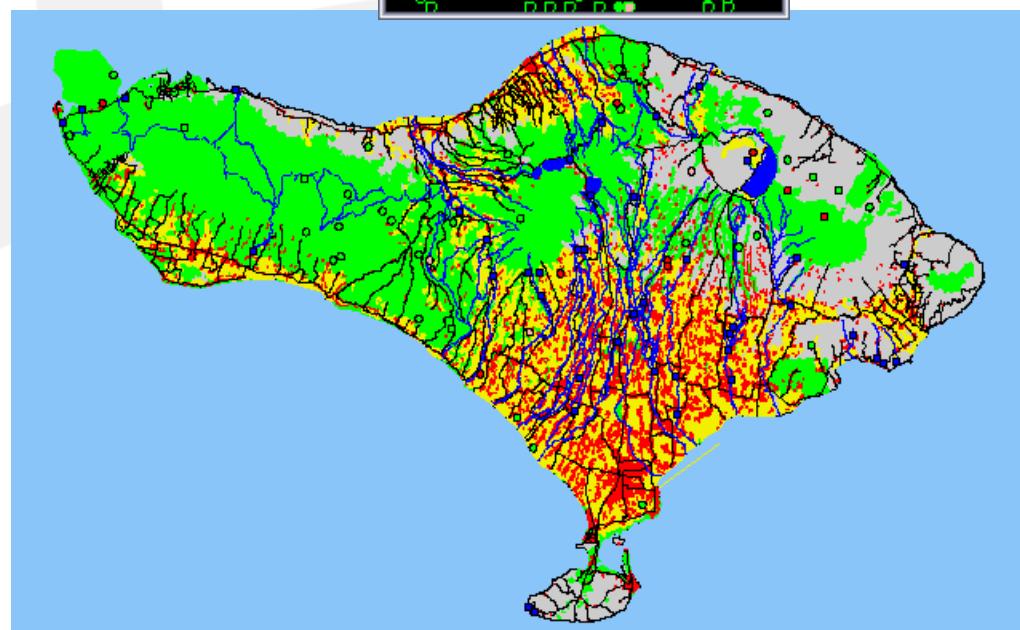
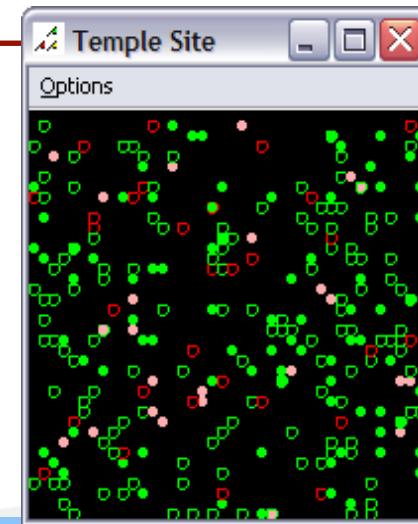
- GIS data (ESRI shapefiles) for 7 types of environment

Model Parameters

- Pathogen
- Movement
- Behavior

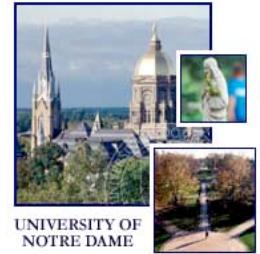
Integration of Tools

- Simulation Environment
 - Repast
- Display
 - OpenMap, Repast
- Spatial Information
 - GeoTools
 - JTS Topology Suite





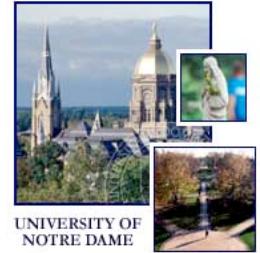
Research Questions



- What are the rate and route of pathogen transmission in macaques across the island?
- How do pathogen life history parameters impact this transmission?
- Do the answers change with inclusion of humans as a component of the landscape?
 - Landscape plays a very important role in each
 - A Complex Adaptive System
 - Work in progress ...



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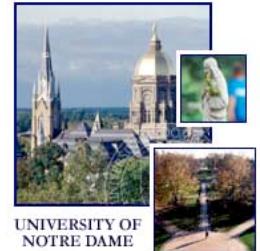
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Disaster Management

The WIPER Prototype



CAS Domain



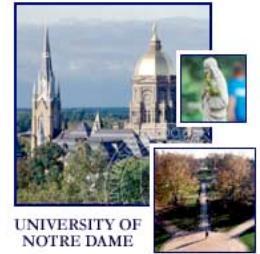
- π Disasters, crises, emergencies, civil disorders, humanitarian relief efforts, transportation disruptions, ... events involving large numbers of people.
 - Natural origins: hurricanes, tornados, earthquakes, tsunami, snow storms, floods, volcanoes, epidemics, ...
 - Human origins: terrorists attacks, political unrest, civil unrest/disorder, industrial accidents, transportation accidents, ...





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Emergency Response Management



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π Problems

- Communication
- Co-ordination
- Situation Awareness (SA)
- Sharing SA

π Information Needs

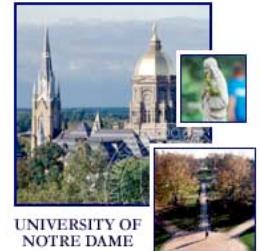
- Alerts - Has something happened?
- Location - Where, extent?
- Numbers - How many people?
- Movement - Stationary, moving?
- What is nature of the event?
- How should we respond?

π Enhanced Situational Awareness and Decision Support





Cell Phones: An In-Place Mobile Sensor Network



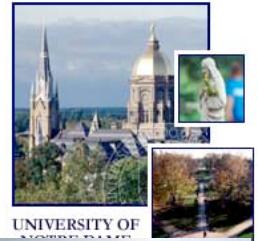
- π Increasing ubiquity in urban areas
- π Approaching +100% in some regions
- π Often more popular than wired systems, especially in developing economies
- π Cell tower and handset continually exchange “signal strength” info
- π Location data
 - Closest cell-tower cells, distance estimates possible
 - Ability to triangulate
 - Growing availability of GPS data
- π Collective knowledge of the location, numbers, calling activity and movement of a large sample of population in a region is potentially available





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WIPER



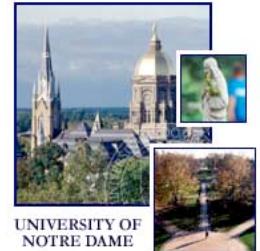
- π Wireless Integrated Phone-Based Emergency Response System
- π Ties into the existing cellular phone infrastructure to detect, monitor, predict anomalies
 - Fact: people make cell phone calls during a disaster
 - Family, friends, E911
 - New calling patterns
 - Increased numbers of calls placed
- π Streaming data
 - Calls placed per cell tower
 - Calling patterns & amount





WIPER/DDDAS

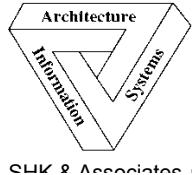
Distributed System Structure



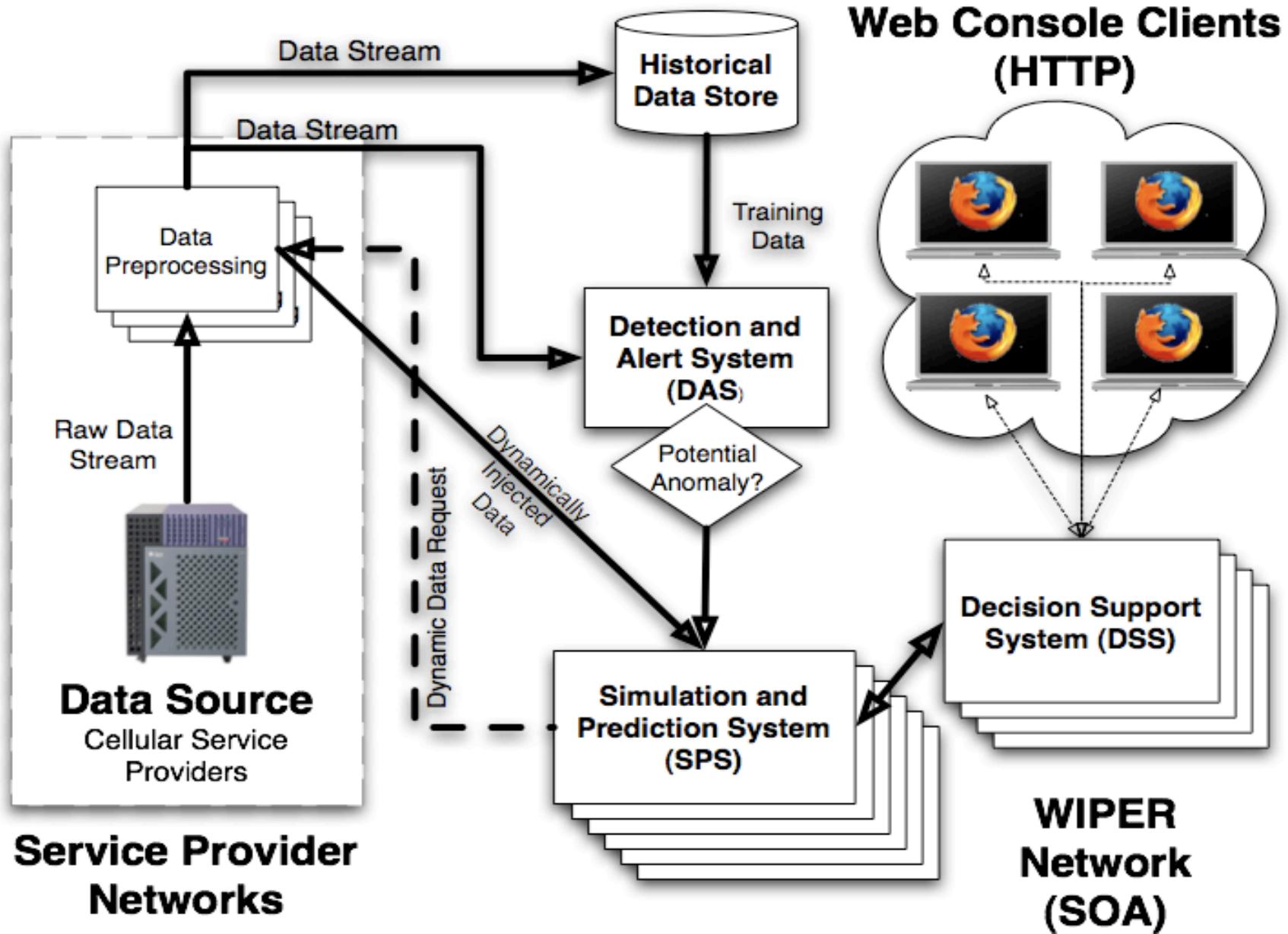
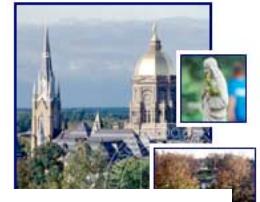
- π Real Time Data Source
 - Historic data from cellular service provider
 - Eventually will use live data streams
- π DAS - Detection and Alert System
- π SPS - Simulation and Prediction System
- π DSS - Decision Support System



Emergency Operations Center (EOC)



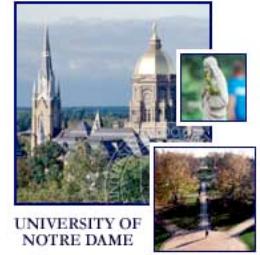
WIPER/DDDAS Design



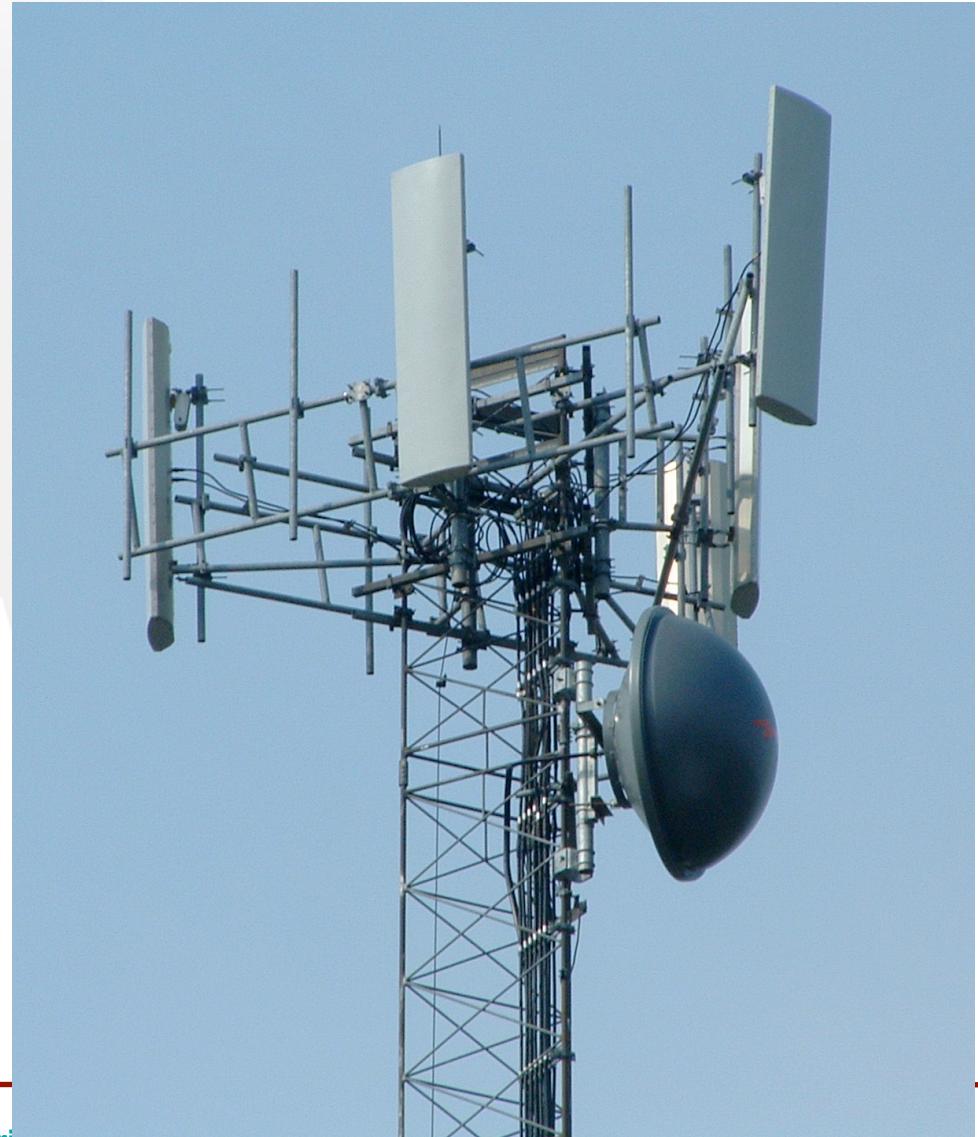


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WIPER - Data Source

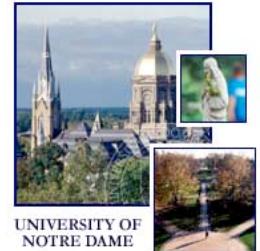


- π Data collection occurs at the cellular service provider
- π WIPER receives anonymized, pre-processed, encrypted data
- π No personally identifiable information leaves the service provider's network

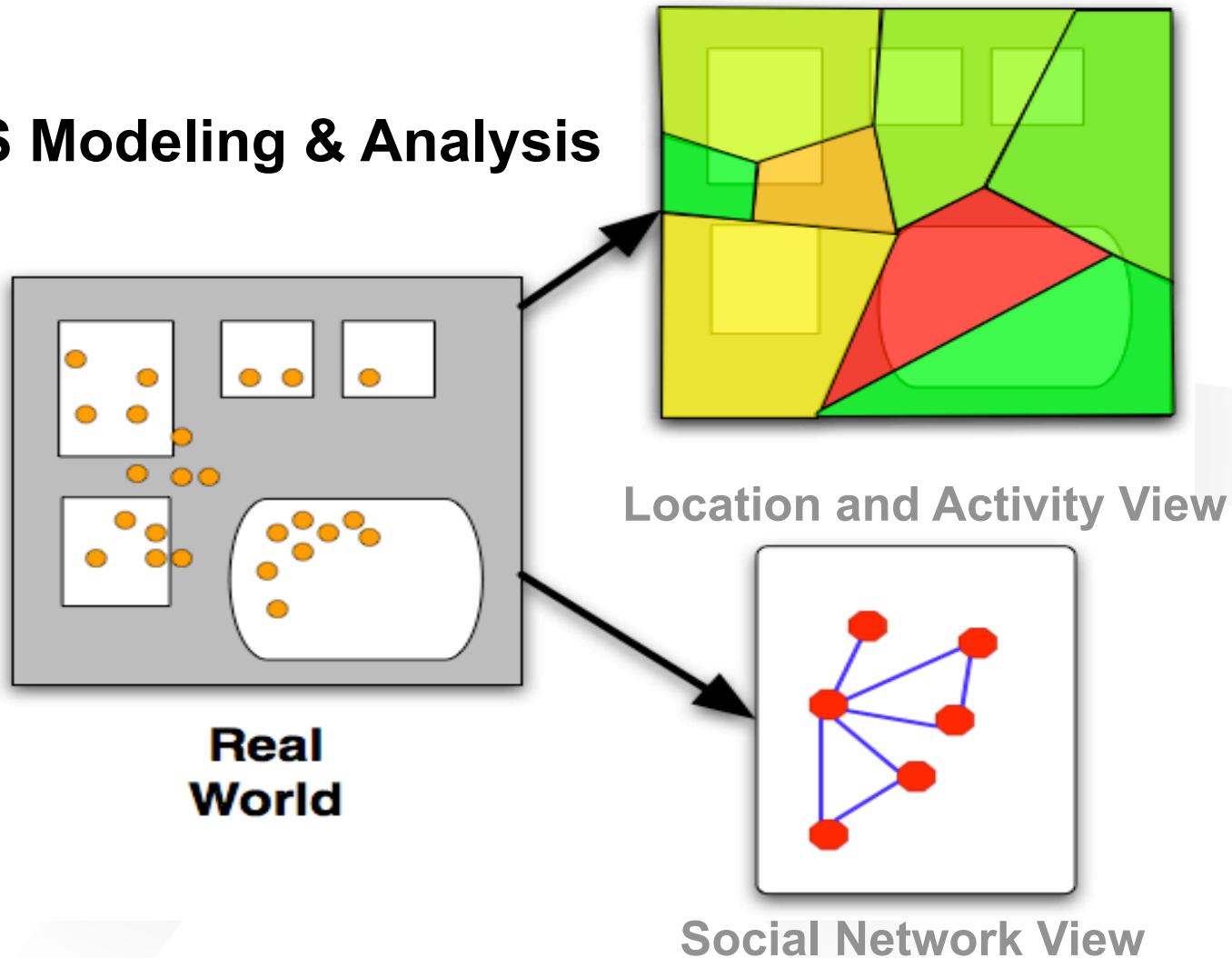




WIPER - Detection and Alert

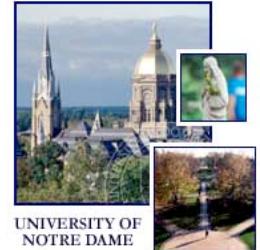


CAS Modeling & Analysis





Simulation Prediction System

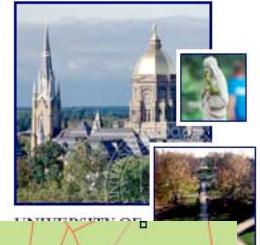


- π For all alerts, WIPER generates an ensemble of Agent-Based Simulations
- π Simulations used to determine nature of anomaly, predict evolution of event
- π Simulations use direct stream of information to monitor real world and dynamically validate/update simulations

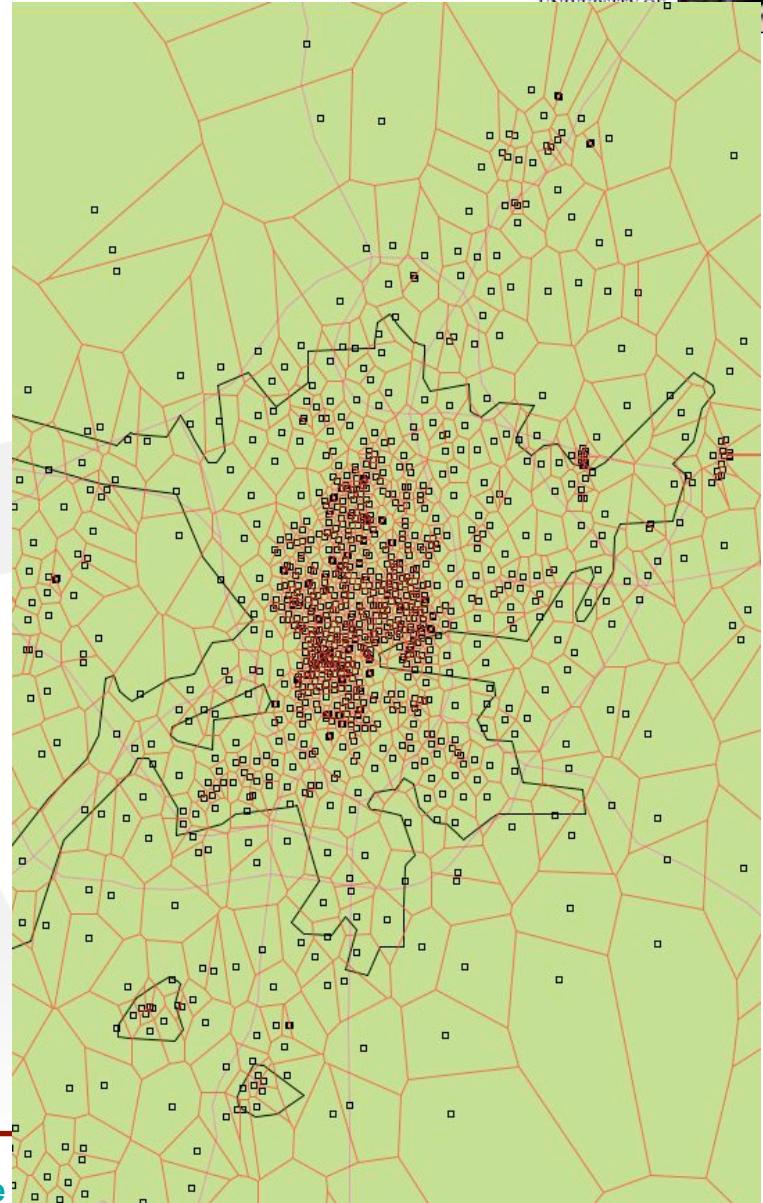




Simulation Prediction System



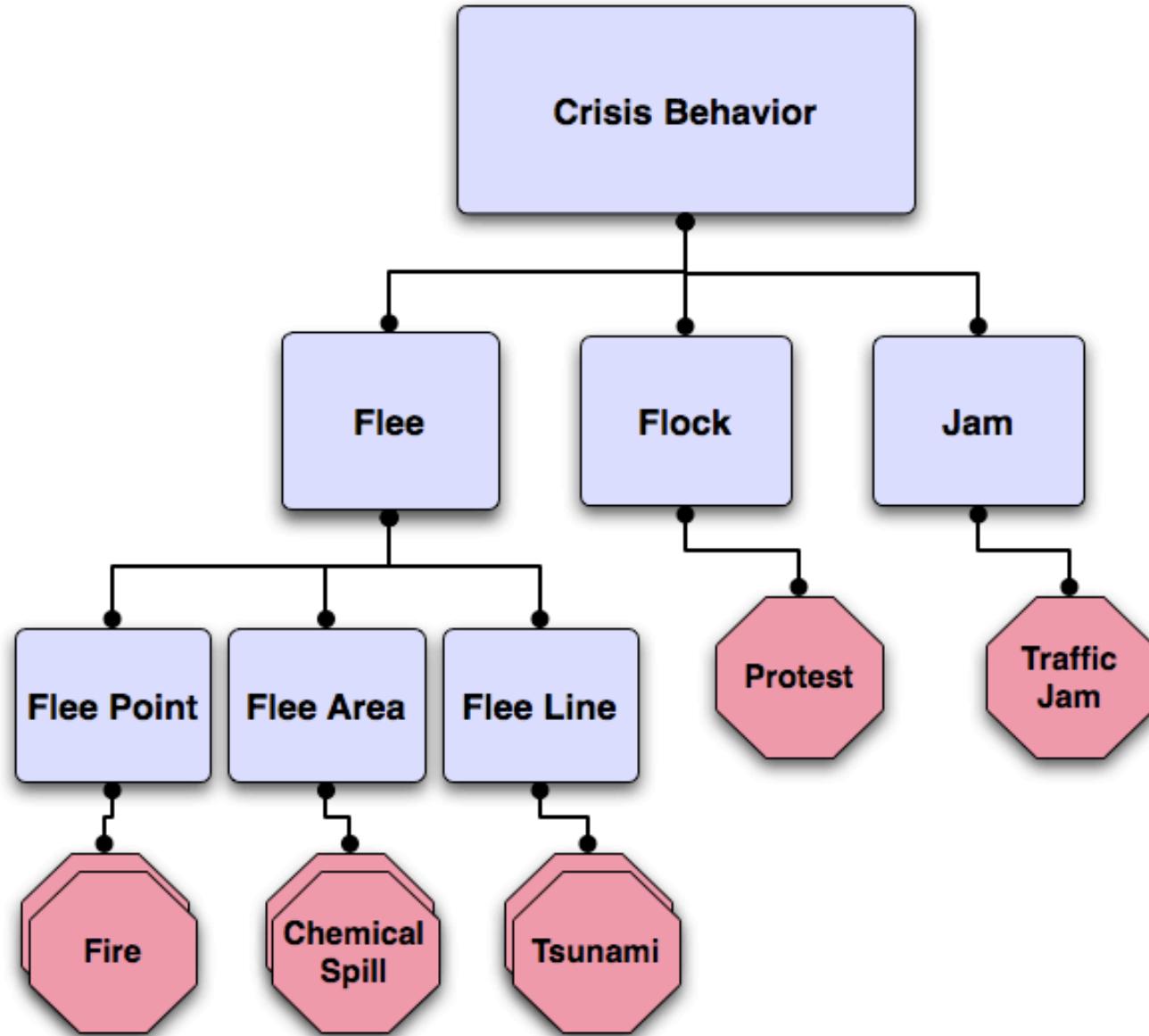
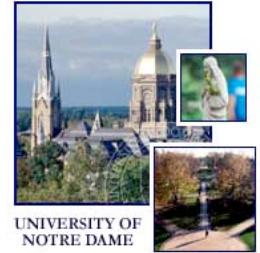
- π Agent-Based/GIS-Based Simulations used to test hypotheses about real-world phenomena
- π Geo-spatial constraints embodied in the simulations
 - Rivers, roads, coast-lines
 - Accurate cell-tower coordinates
 - Overlaid on maps to support emergency response managers

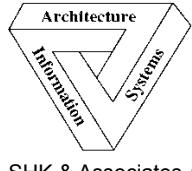




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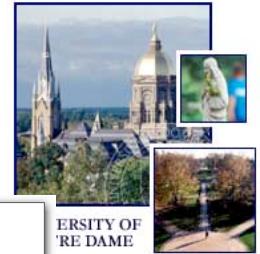
Crises Taxonomy





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Decision Support System



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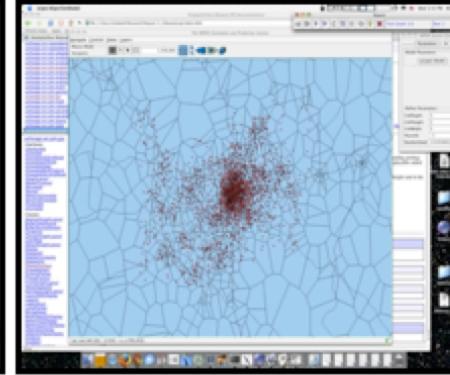
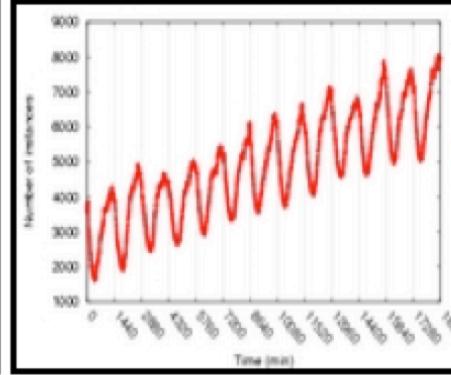
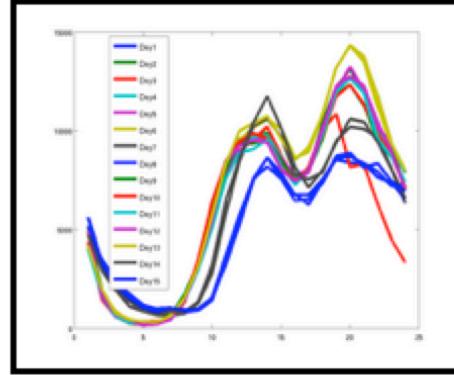
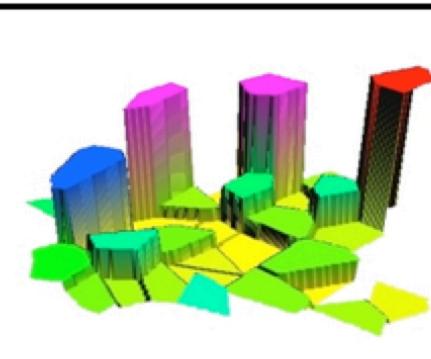
Welcome Maps Log Files GIS Status Call Activity Data Analysis Simulation Resources RSS Feed



The WIPER Emergency Management System

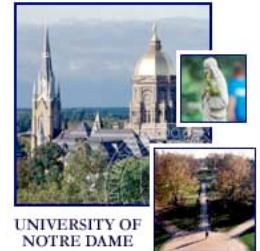


Date/Time	SMP	PIR	P2R	TMP	Pwr	P10
02/05/01 09:40 AM	99	20	7	49	99 OFF	0
02/05/01 09:40 AM	88	13	10	60	82 OFF	0
02/05/01 09:40 AM	79	5	19	63	88 OFF	0
02/05/01 09:41 AM	72	0	24	70	76 OFF	0
02/05/01 09:41 AM	71	7	29	73	74 OFF	0
02/05/01 09:41 AM	67	6	35	78	67 OFF	0
02/05/01 09:41 AM	56	9	38	83	64 OFF	0
02/05/01 09:41 AM	45	20	45	93	58 OFF	0
02/05/01 09:41 AM	42	29	54	100	54 OFF	0
02/05/01 09:42 AM	35	31	63	92	49 OFF	0
02/05/01 09:42 AM	31	38	69	95	42 OFF	0
02/05/01 09:42 AM	26	41	68	80	38 OFF	0
02/05/01 09:42 AM	21	53	72	81	37 OFF	0
02/05/01 09:42 AM	10	58	83	70	36 OFF	0
02/05/01 09:42 AM	3	68	92	60	38 OFF	0





Decision Support System



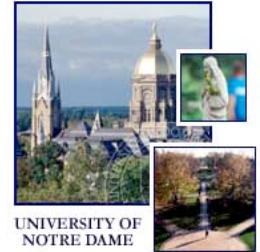
- π Web-based console that provides access to real-world info, results from simulations
- π Emergency responders can compare the real-world information with the simulation predictions, decide course of action
- π If desired, console can be shared with responders in the field over encrypted web connection
- π Alerts could be sent from DSS directly to cell phones in affected area



- **Geo-spatial data - maps of crises area**
- **Temporal data - timelines, events**
- **Numerical data - graphs, charts, tables**
- **Predictions - animations**



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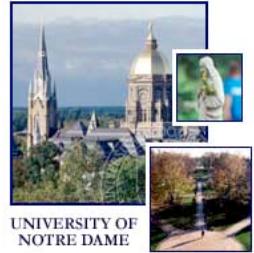
Example of CAS Methods Supporting a Research Investigation

Understanding the SourceForge.net Open Source Software Development Community



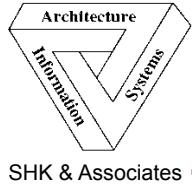
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Outline

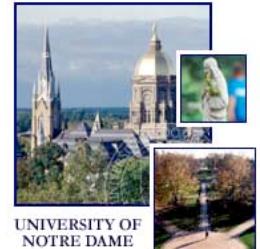


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- π Introduction & Background
- π Research data description
- π Research methods
 - Social Network Analysis
 - Agent-based Simulation
 - The “Computer Experiment” – *in silico*
- π Experimental results
 - Hypothesis/Model I
 - Hypothesis/Model II
 - Hypothesis/Model III
- π Summary and discussion



Background (OSS)



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π What is OSS?

- Free to use, modify and distribute
- Source code available and modifiable

π Potential advantages over commercial software

- High quality
- Fast development
- Low cost

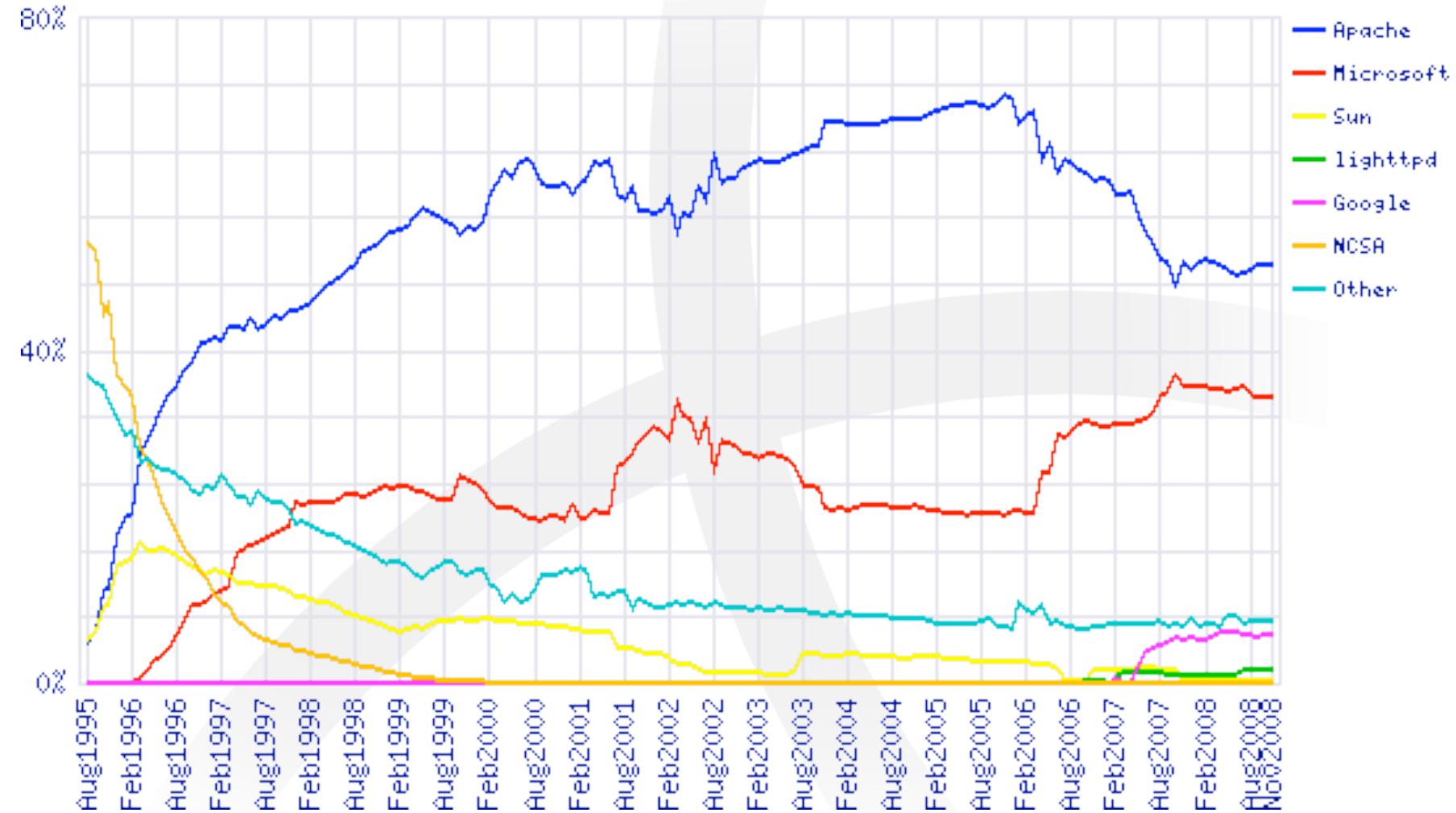
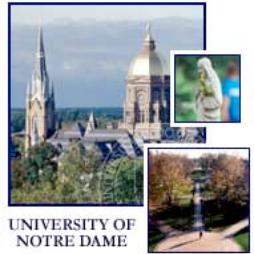
π Why study OSS?

- **Complexity — an example of self-organization/ emergence**
- Software engineering — new development and coordination methods
- Open content — model for other forms of open, shared collaboration
- Economic motivations, virtual teams, organizational behavior, patent and intellectual property, etc.

Evidence of adoption and popularity is Apache-->



Number of Active Apache Hosts



Open Source Software (OSS)



Savannah



Free ...

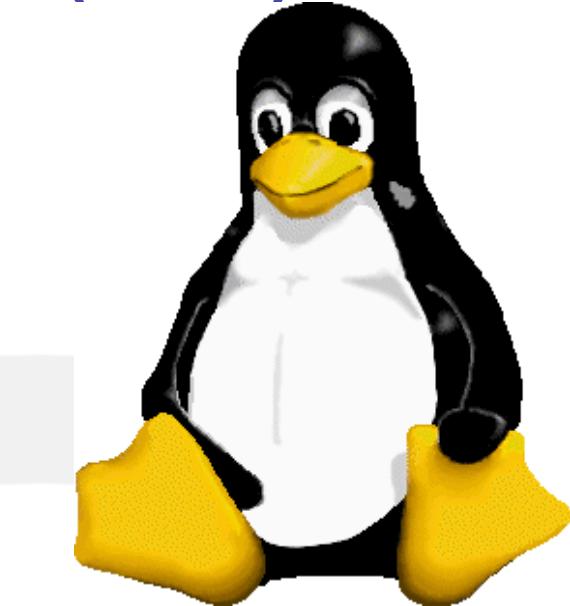
- to view source
- to modify
- to share
- of cost

Examples

- Apache
- Perl
- GNU
- Linux
- Sendmail
- Python
- KDE
- GNOME
- Mozilla
- Thousands more



RePast



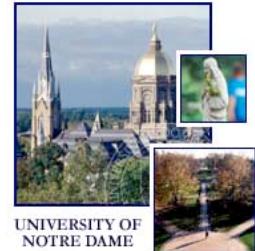
The Apache Software Foundation

<http://www.apache.org/>

Python



Research Data



 **SourceForge.net**
Create, Participate, Evaluate

Registered Projects: 144,548 Registered Users: 1,545,019

SourceForge Is Hiring 

Project of the Month  Zenoss Core

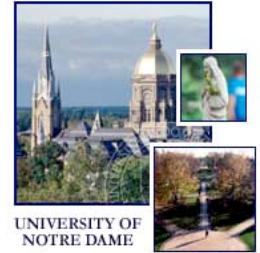
- π SourceForge.net community
 - The largest OSS development community
 - Over 163,000 registered projects
 - Over 2 million registered users
- π SourceForge.net Research Archive (SRDA)
 - <http://zerlot.cse.nd.edu/>
 - <http://www.nd.edu/~oss/Data/>
 - 600 GB of data
 - Open to scholarly researchers

<http://sourceforge.net/>
October 27, 2008





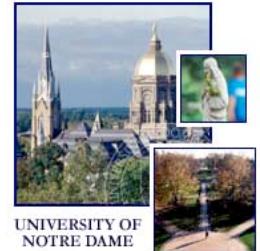
Collaboration Social Networks



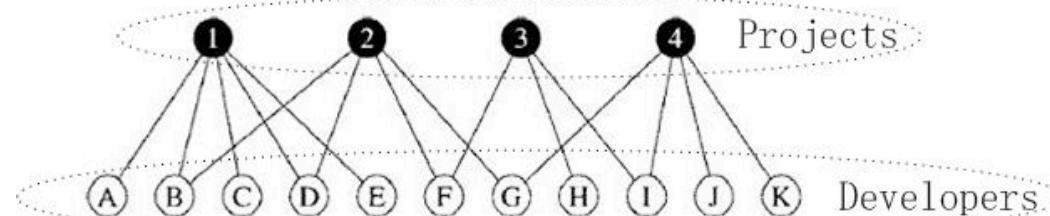
- π What is a collaboration network?
 - A social network representing the collaborating relationships
 - Movie actor network
 - Kevin Bacon number
 - Research paper authorship network
 - Erdős number in mathematics
 - Open source software developers/projects
- π Differences in the SourceForge collaboration network
 - Link detachment
 - Virtual collaboration
 - Open source software
- π Bipartite/unipartite properties of collaboration networks



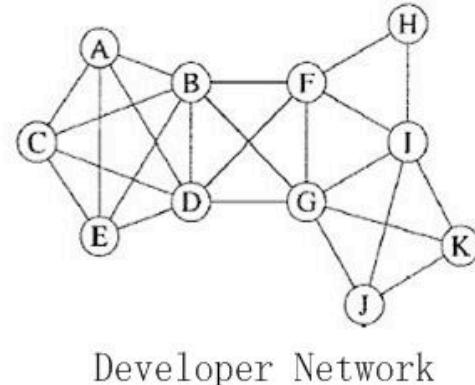
Collaboration Networks Bipartite and Unipartite



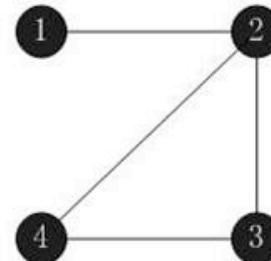
C-Net



D-Net



Developer Network



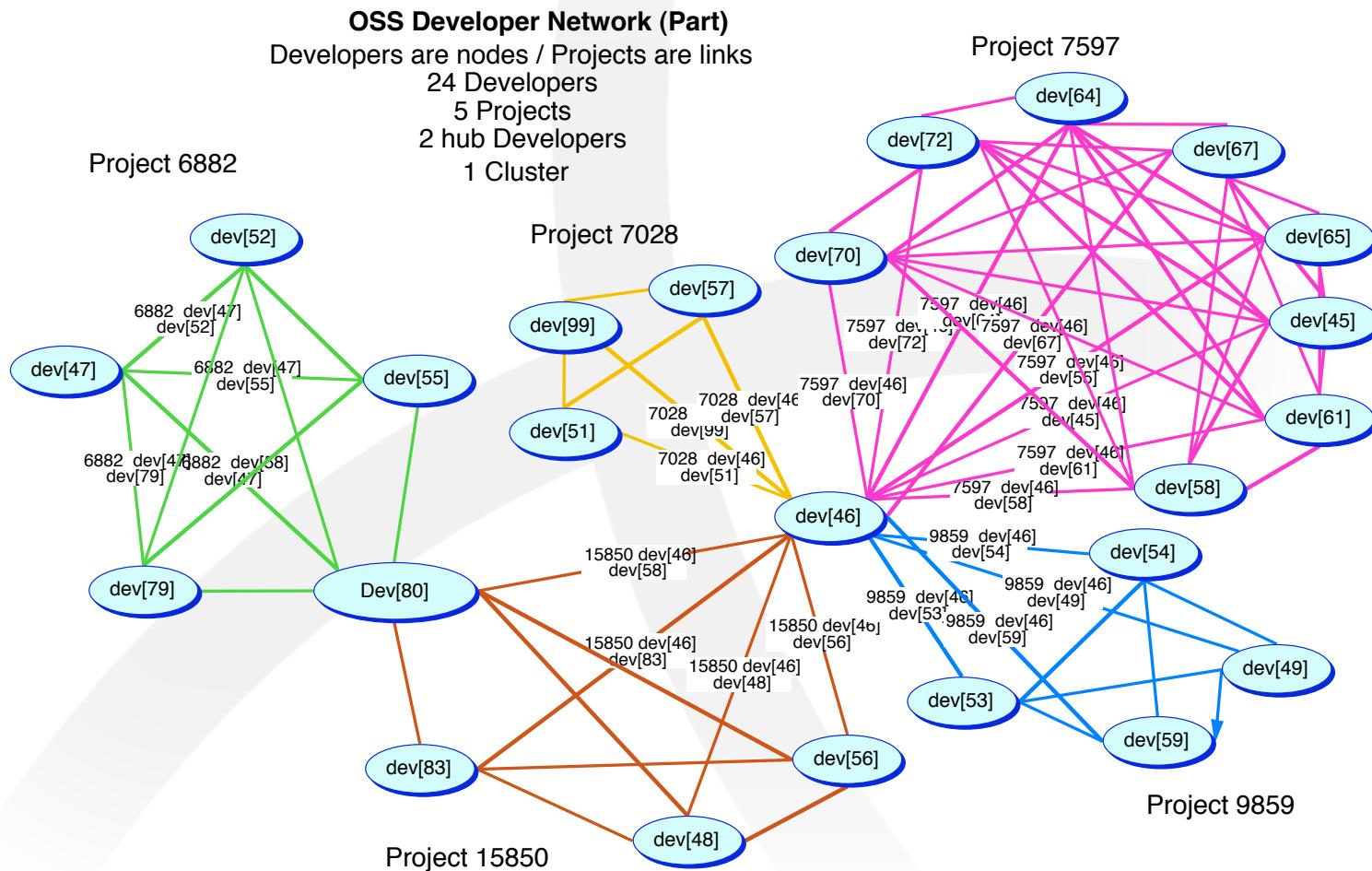
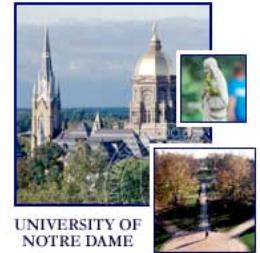
Project Network

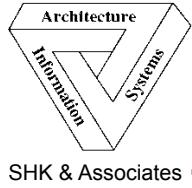
P-Net

Adapted from Newman, Strogatz and Watts, 2001



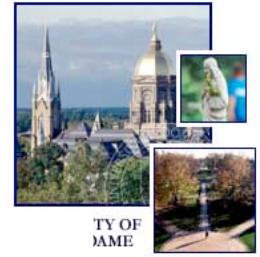
SourceForge Developer Collaboration Network (a cluster)



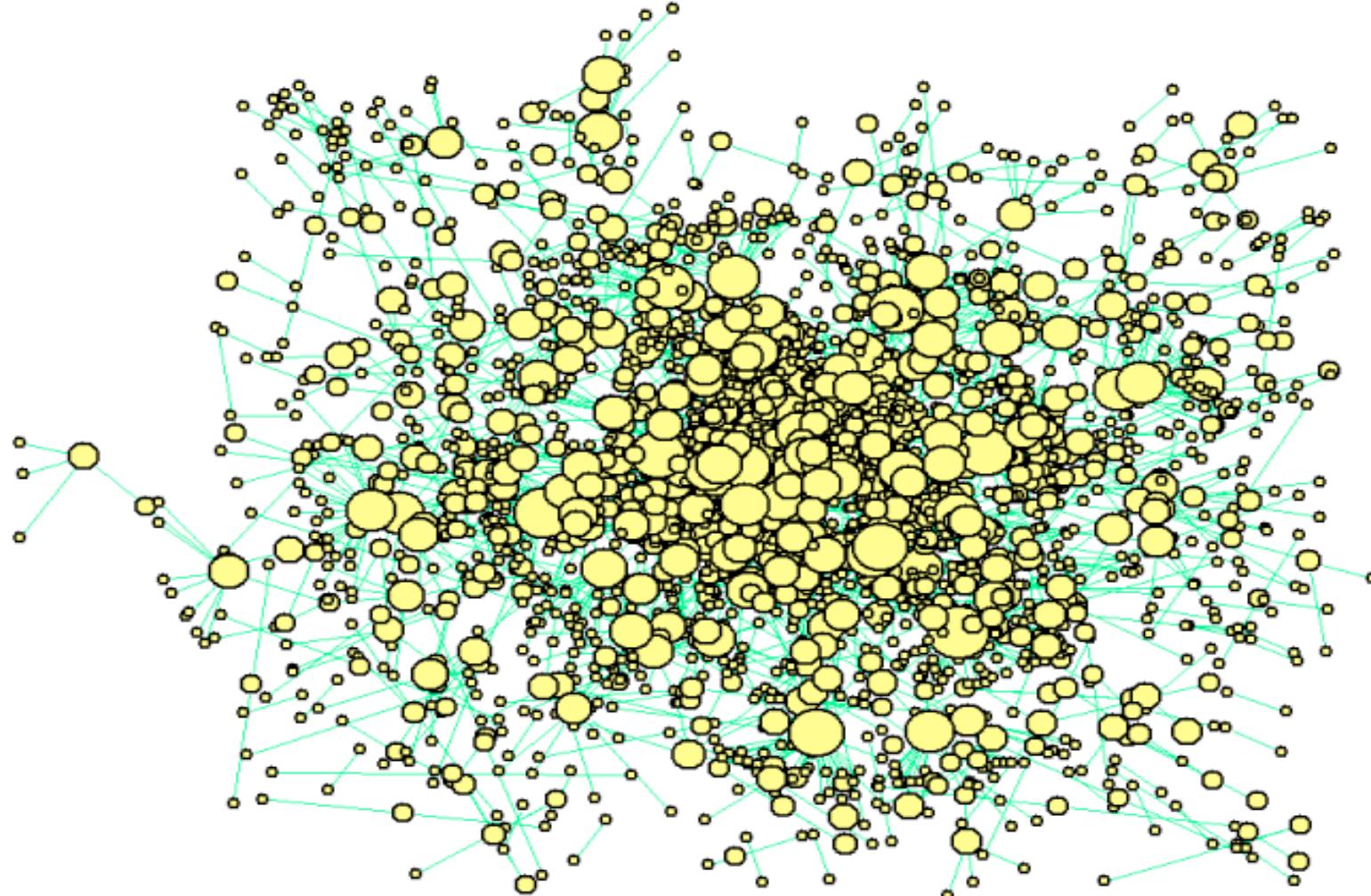


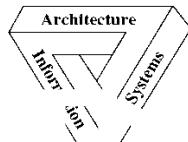
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Another Cluster



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The New York Times



March 4, 2003

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The Real Scientific Hero of 1953

By STEVEN STROGATZ

THACA, N.Y.

Last week newspapers and magazines devoted tens of thousands of words to the 50th anniversary of the discovery of the chemical structure of DNA. While James D. Watson and Francis Crick certainly deserved a good party, there was no mention of another scientific feat that also turned 50 this year — one whose ramifications may ultimately turn out to be as profound as those of the double helix.

In 1953, Enrico Fermi and two of his colleagues at Los Alamos Scientific Laboratory, John Pasta and Stanislaw Ulam, invented the concept of a "computer experiment." Suddenly the computer became a telescope for the mind, a way of exploring inaccessible processes like the collision of black holes or the frenzied dance of subatomic particles — phenomena that are too large or too fast to be visualized by traditional experiments, and too complex to be handled by pencil-and-paper mathematics. The computer experiment offered a third way of doing science. Over the past 50 years, it has helped scientists to see the invisible and imagine the inconceivable.

TIMES NEWS TRACKER

Topics

Fermi, Enrico

[Create](#)

DNA (Deoxyribonucleic Acid)

[Create](#)

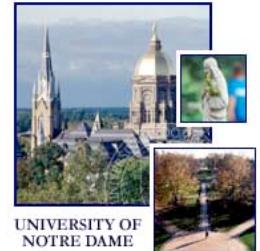
Science and Technology

[Create](#)

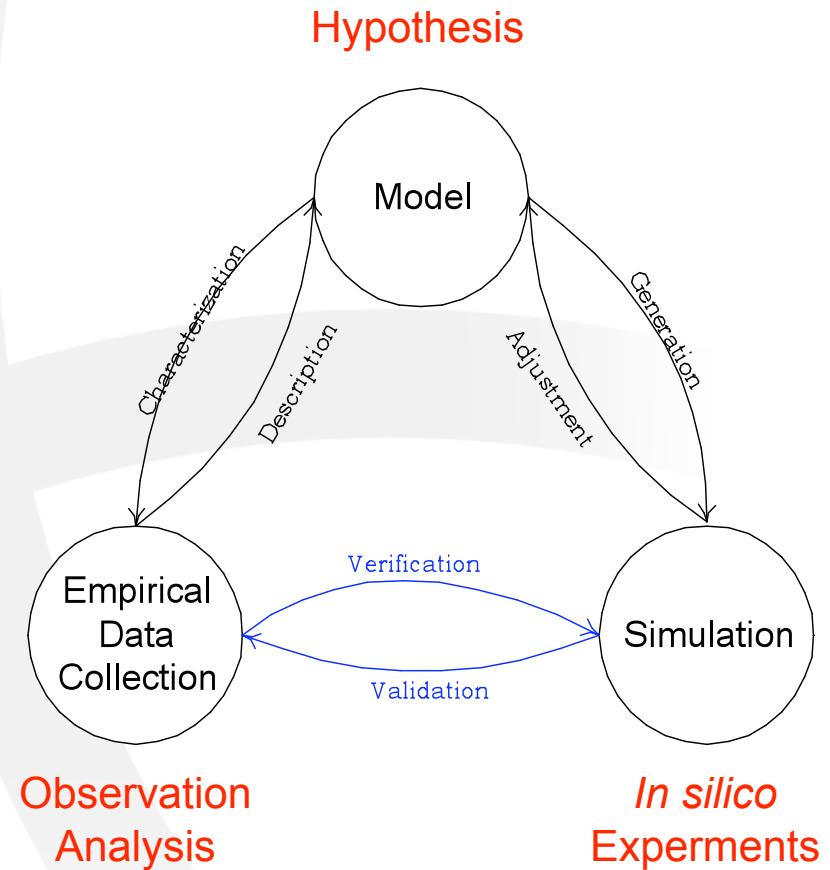
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Research Methods



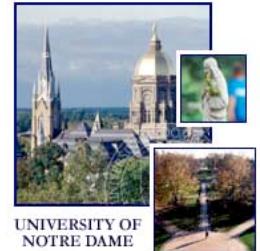
- π Iterative simulation method
 - Empirical dataset
 - Model
 - Simulation
- π Verification and validation
 - More measures
 - More methods
- π Analogous to the development of engineering simulations



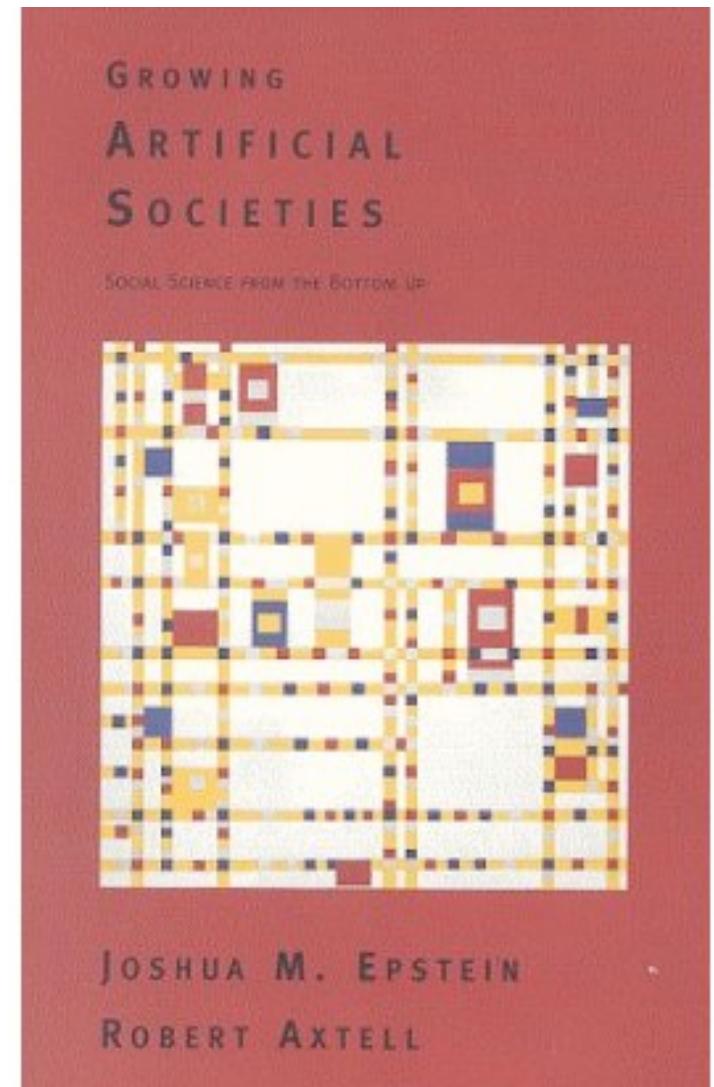


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Model of SourceForge.net



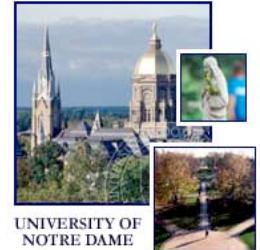
- π ABM based on unipartite graph
- π Grow Artificial SourceForge.net's to evaluate hypotheses about evolution of real-world SourceForge.net
- π Model description
 - Agents: developers with randomized characteristics
 - Behaviors: create, join, abandon and idle
 - Projects: have attractiveness / characteristics
 - Developers: have preferences / characteristics
- π Previous: Four models / hypotheses
 - ER, BA, BA with constant fitness and BA with dynamic fitness
- π New: Three models / hypotheses
- π Comparison of observed and simulated social networks
 - Social network properties
 - Measures of graph (network) characteristics





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Model I



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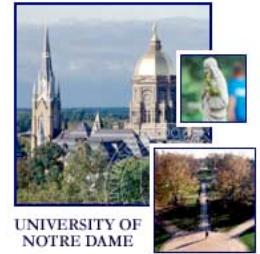
π Description

- Realistic stochastic procedures.
 - New developer every time step based on Poisson distribution
 - Initial fitness based on log-normal distribution
- Updated procedure for the weighted project pool (for preferential selection of projects).



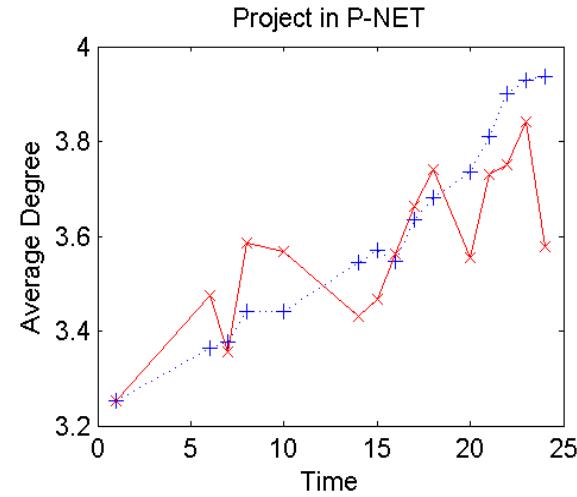
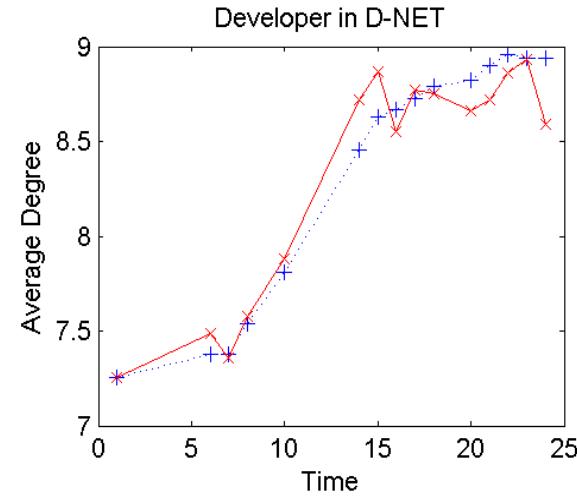
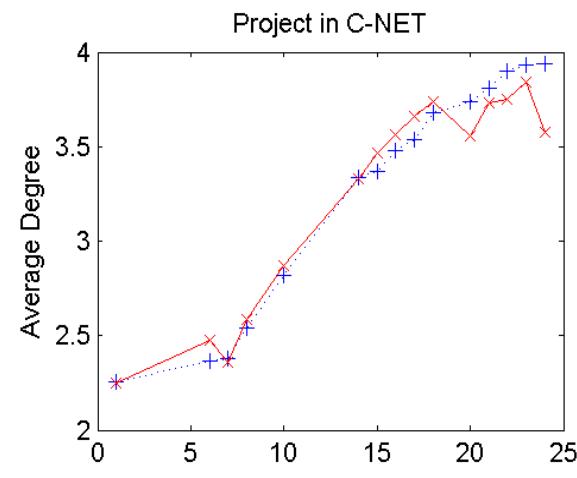
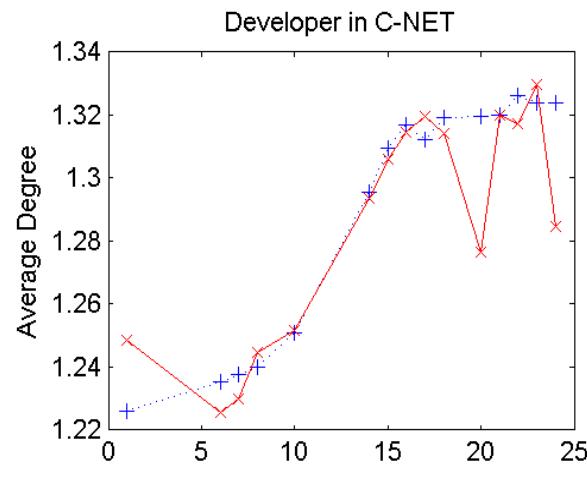
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Results: Model I



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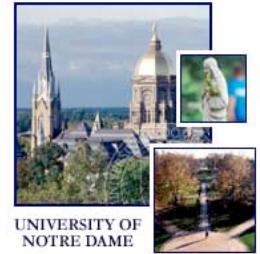
π Average degrees





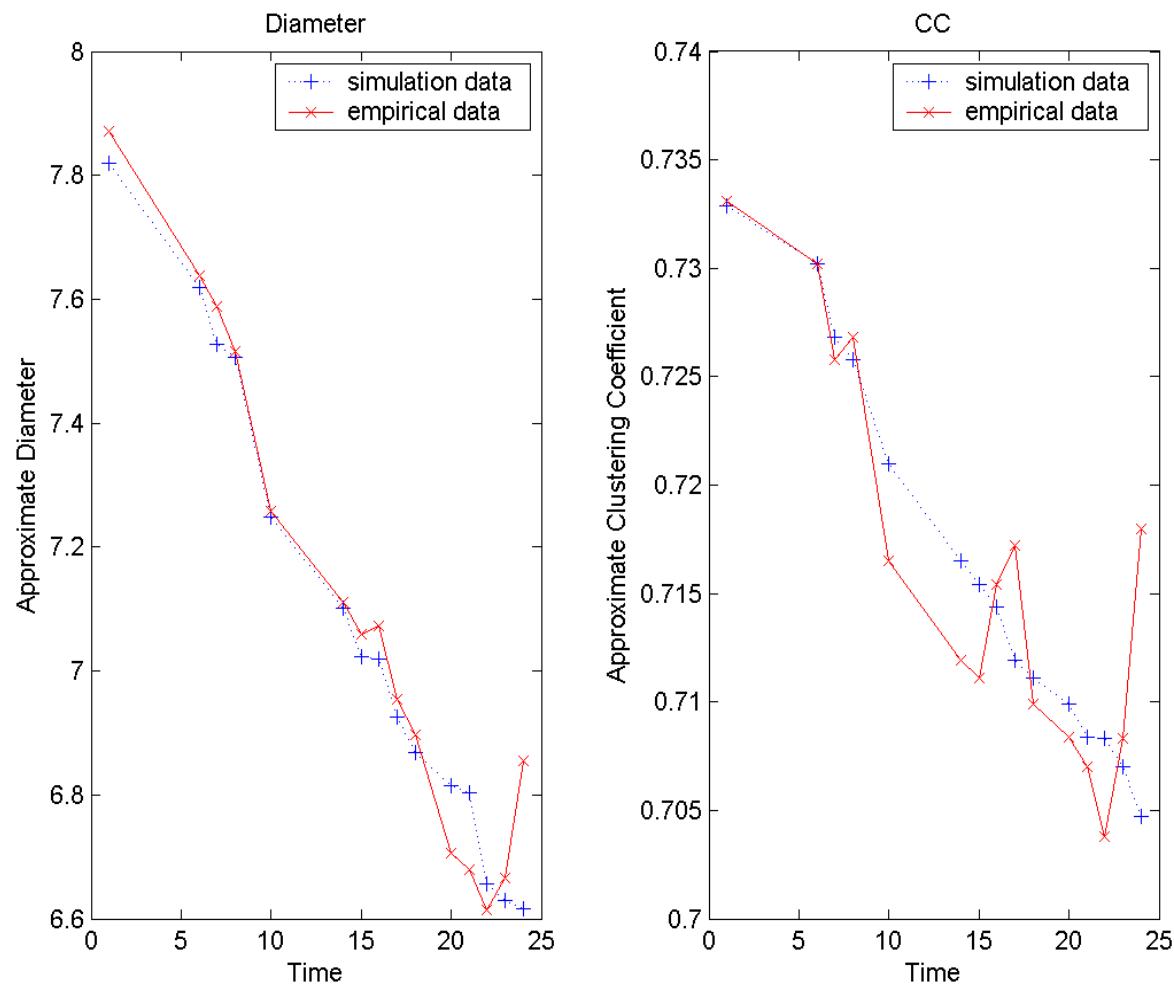
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Results: Model I



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π Diameter and CC

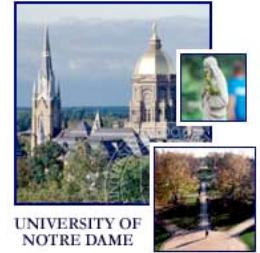


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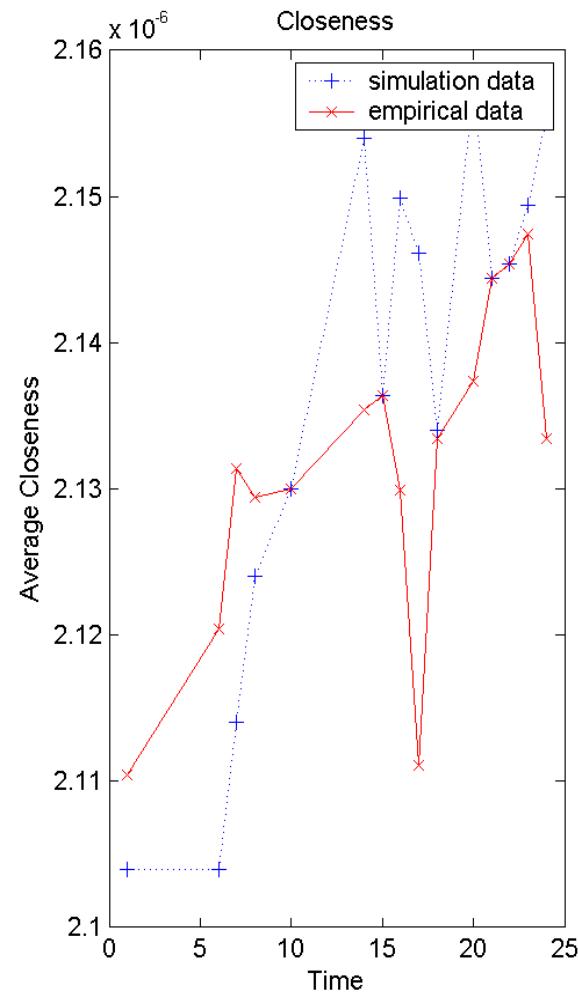
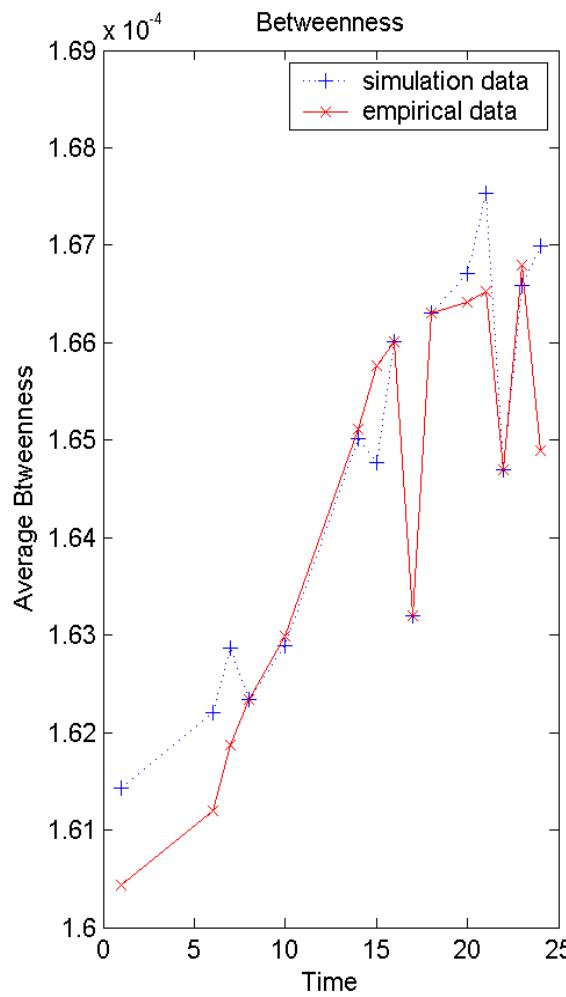
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Results: Model I



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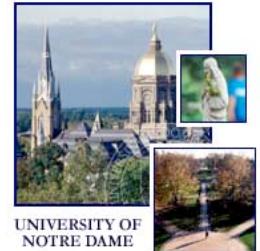
π Betweenness and Closeness





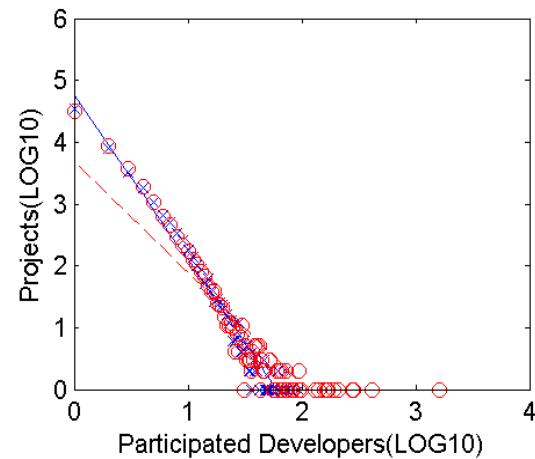
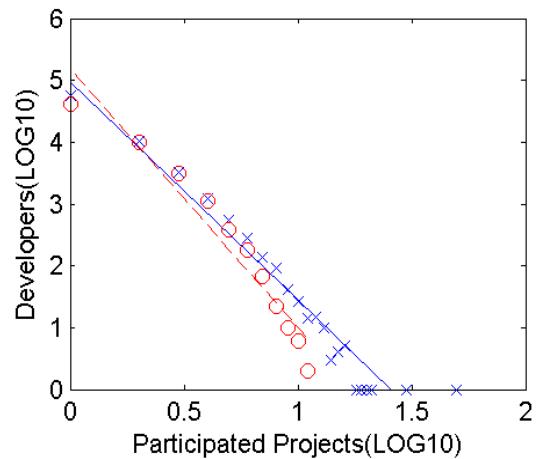
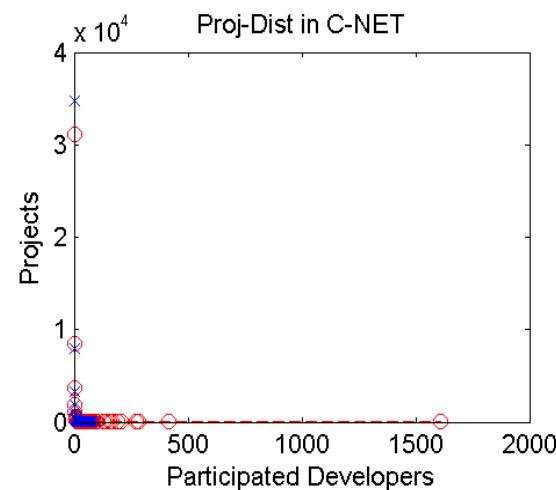
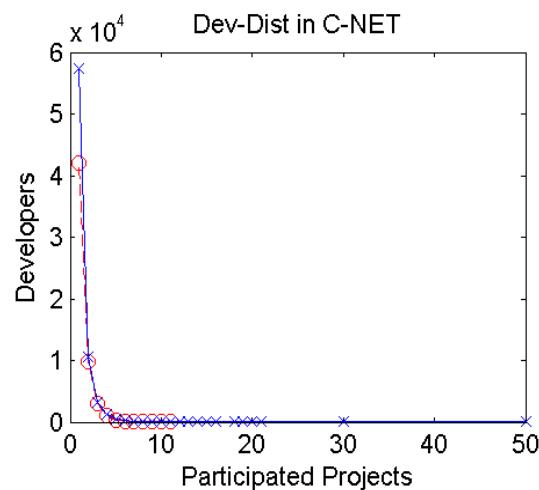
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Results: Model I



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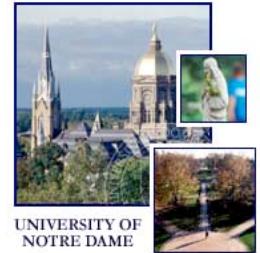
π Degree Distributions





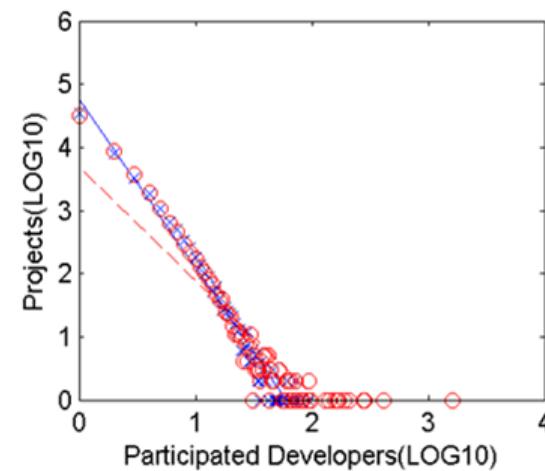
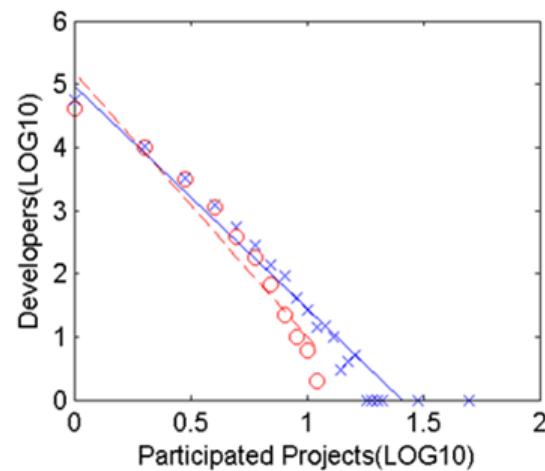
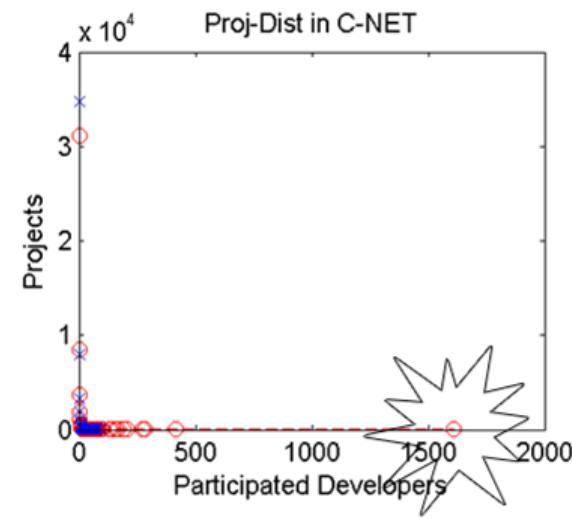
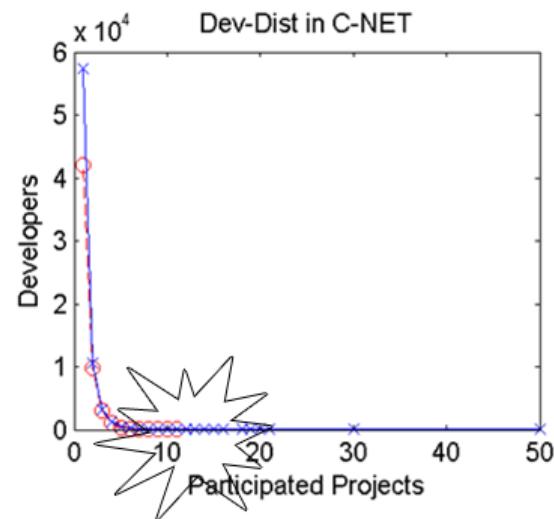
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Results: Model I



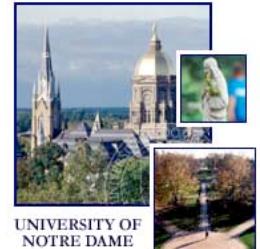
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π Problems





Model II



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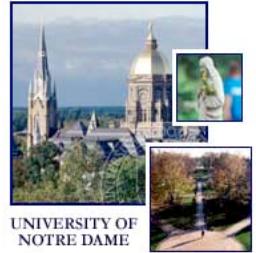
π Description

- New addition: user energy.
- User energy
 - The “fitness” parameter for the user
 - Every time a new user is created, a energy level is randomly generated for the user
 - Energy level will be used to decide whether a user will take a action or not during every time step.



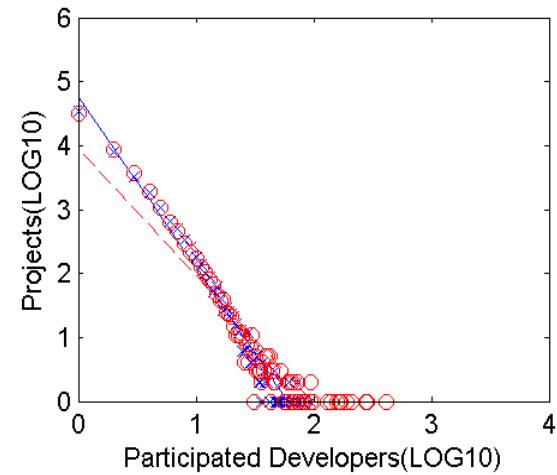
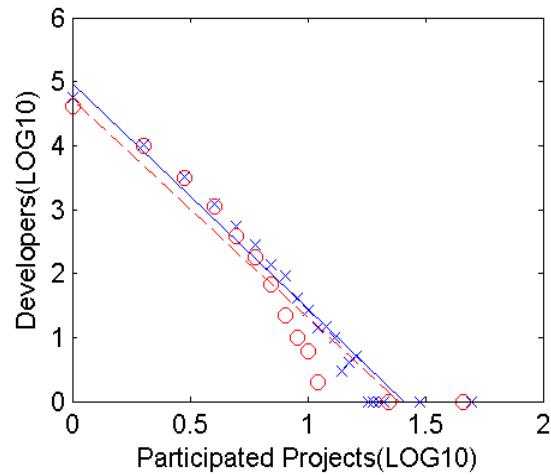
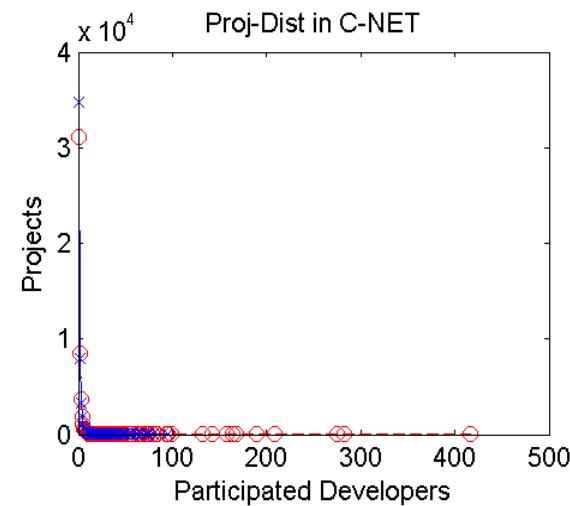
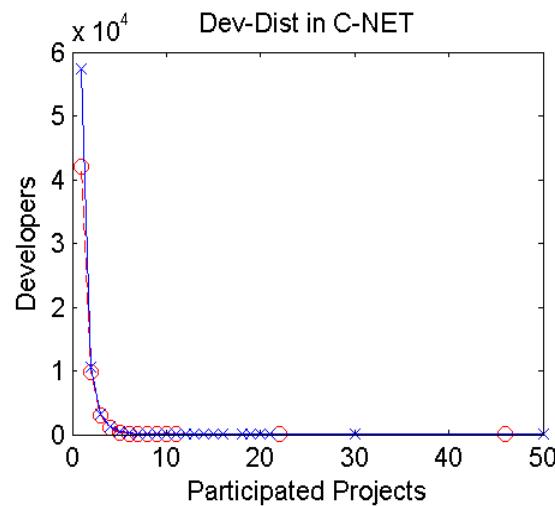
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Results: Model II



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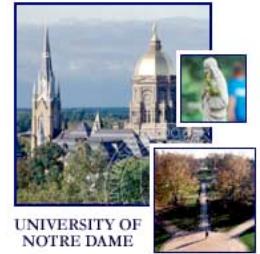
π Degree distributions



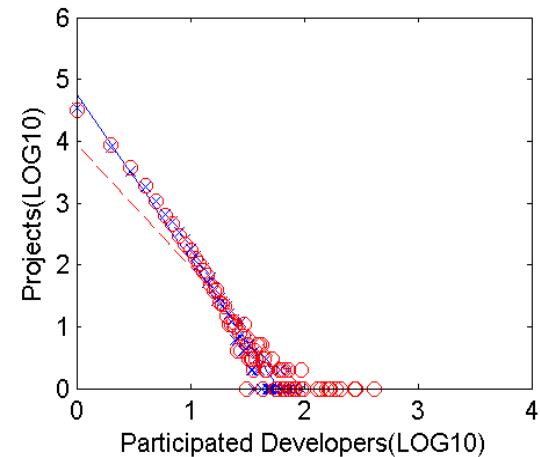
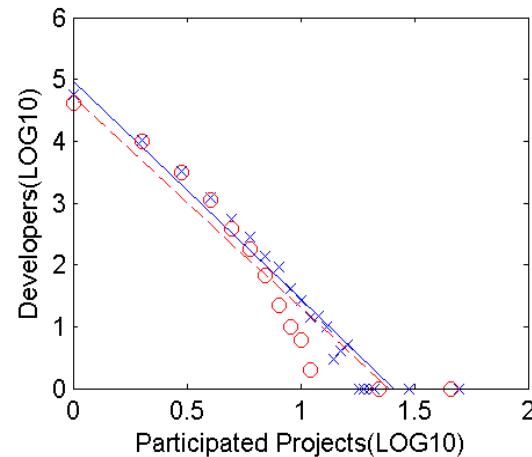
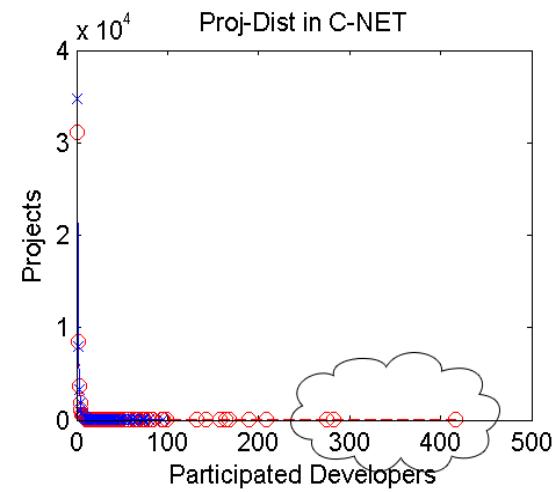
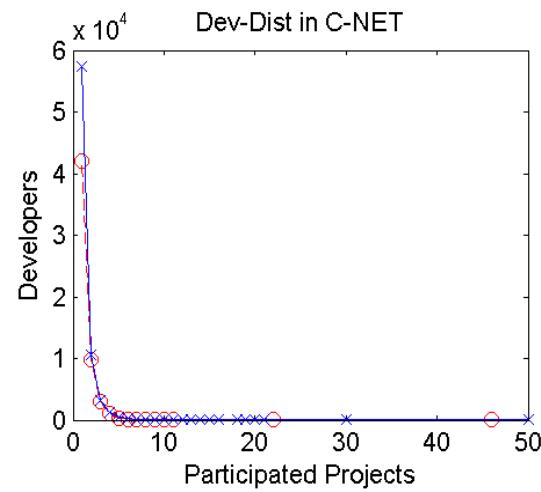


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Results: Model II



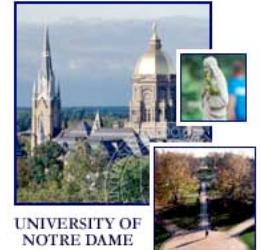
- π Better, but still has problems





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Model III



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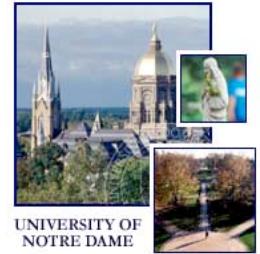
π Description

- New addition: dynamic user energy.
- Dynamic user energy
 - Decaying with respect to time
 - Self-adjustable according to the roles the user is taking in various projects.



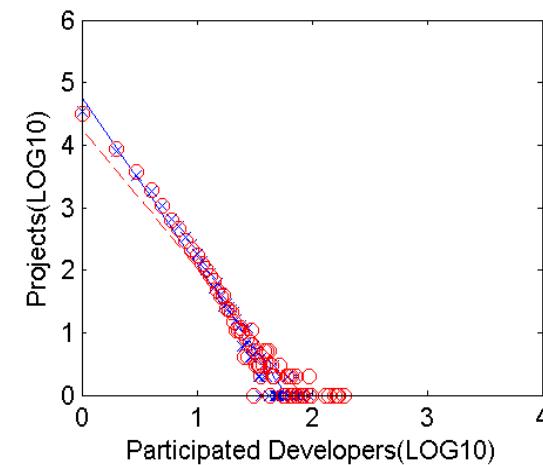
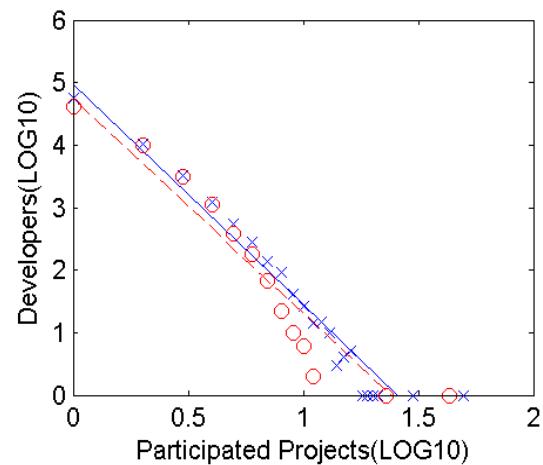
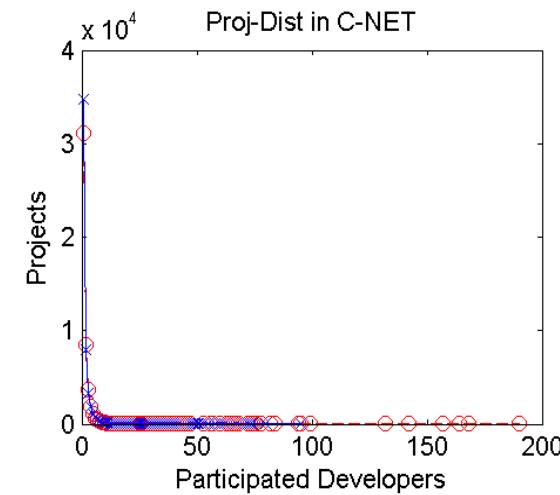
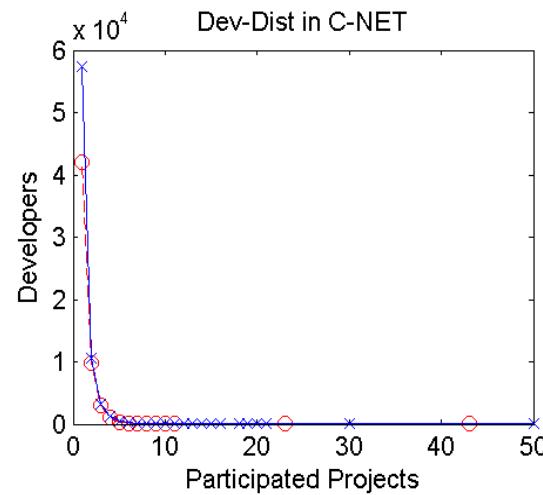
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Results: Model III



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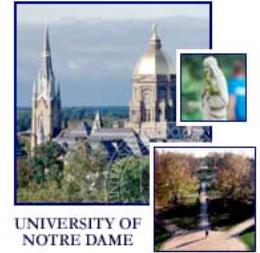
π Degree distributions





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Summary

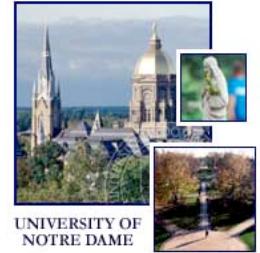


Models	Measures	Patterns in Data	Simulated Patterns
Model I (more realistic distributions)	Developer Distribution	Power Law (large tail)	Power Law (small tail)
	Project Distribution	Power Law (small tail)	Power Law (large tail)
	Average Degrees	Increasing	Increasing
	Clustering Coefficient	Decreasing	Decreasing
	Diameter	Decreasing	Decreasing
	Average Betweenness	Decreasing	Decreasing
	Average Closeness	Decreasing	Decreasing
Model II (constant user energy)	Developer Distribution	Power Law (large tail)	Power Law (large tail)
	Project Distribution	Power Law (small tail)	Power Law (reasonable tail)
	Average Degrees	Increasing	Increasing
	Clustering Coefficient	Decreasing	Decreasing
	Diameter	Decreasing	Decreasing
	Average Betweenness	Decreasing	Decreasing
	Average Closeness	Decreasing	Decreasing
Model III (dynamic user energy)	Developer Distribution	Power Law (large tail)	Power Law (large tail)
	Project Distribution	Power Law (small tail)	Power Law (small tail)
	Average Degrees	Increasing	Increasing
	Clustering Coefficient	Decreasing	Decreasing
	Diameter	Decreasing	Decreasing
	Average Betweenness	Decreasing	Decreasing
	Average Closeness	Decreasing	Decreasing



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Discussion



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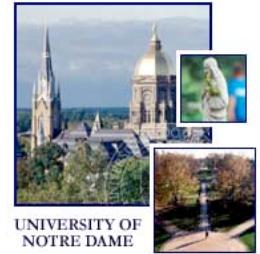
π Results/Discussion

- Expanding the network models for modeling evolving complex networks (more hypotheses and computer experiments)
- Provided a validated model to simulate the collaboration network at SourceForge.net
- Demonstration of the use of “computer experiments” for scientific research using agent-based modeling --> analogous to the development of engineering simulations
- Research approach that can be used to study other OSS communities or similar collaboration networks
- Demonstrated the use of various network metrics for V&V of agent simulations
- Resources/references:
 - <http://www.nd.edu/~oss/Papers/papers.html>
 - <http://zerlot.cse.nd.edu/mywiki/>



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Related Work



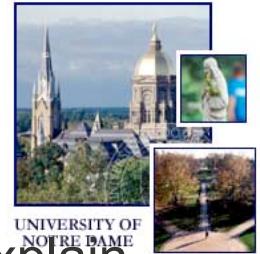
π Related Research:

- P.J. Kiviat, “Simulation, technology, and the decision process”, *ACM Transactions on Modeling and Computer Simulation*, 1991.
- R. Albert and A.L. Barabási, “Emergence of scaling in random networks”, *Science*, 1999.
- J. Epstein R. Axtell, R. Axelrod and M. Cohen, “Aligning simulation models: A case study and results”, *Computational and Mathematical Organization Theory*, 1996.



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Some Thoughts on Models



- π Models are a way to discover new ways by which one might explain things, and to create new questions. They are NOT representations of the "real world", nor are they intended to be.
- π Careful and deliberate collection of observations is, in many cases, as important in drawing conclusions from models as it is in drawing conclusions about the world.
- π Good models are at least as important for what they make one wonder about that one might not have wondered about as they are for what they allow one to conclude.
- π Modelling, like science in general, is fundamentally a social activity

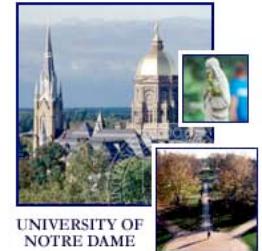
<http://serendip.brynmawr.edu/complexity/models/segitseg/tips.html>



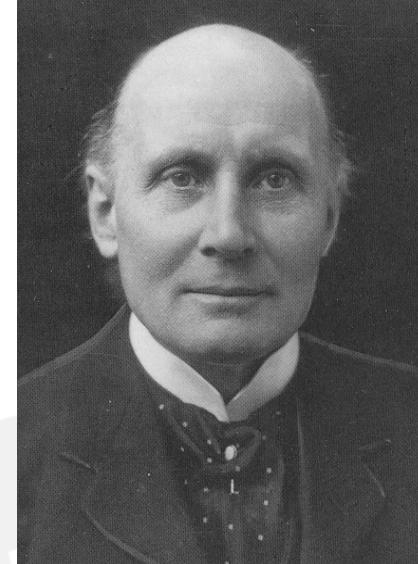
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A Final Word!

Alfred North Whitehead



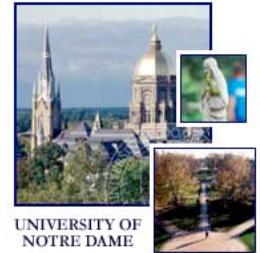
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We have a tendency to mistake our models for reality, especially when they are good models.

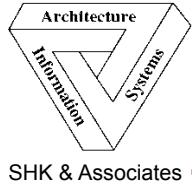


Thus, we observe ...

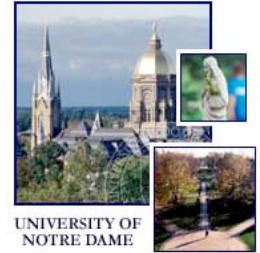


“God chose to give all the easy problems to the physicists.”

—Michael Lave & Jim March, *Introduction to Models in the Social Sciences*



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Thank You

- Greg and Steve -

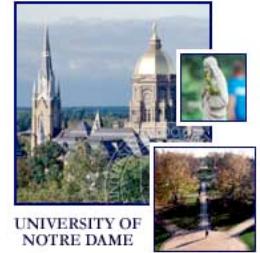


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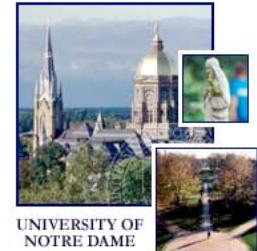
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Additional Information

Wicked Problems (Explained)



π Wicked problems cannot be formulated definitively.

Attempting to formulate the problem essentially is the same as attempting to formulate a solution. Each attempt at generating a solution changes the understanding of the problem – and is the only way to better understand the problem.

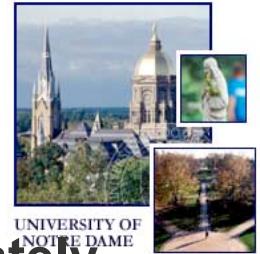
π Wicked problems have no stopping rules.

Because the problem cannot be defined, or can be defined only progressively, it lacks clear stopping rules. Indeed factors such as an exhaustion of resources, or loss of stakeholder interest or political support are more likely to end the problem-solving process than the attainment of a solution.

π Solutions are not true-or-false but good-or-bad.

There are no clear and unambiguous criteria for deciding whether the problem is resolved, so outcomes cannot be judged to be right or wrong. Instead, satisficing stakeholders is a more realistic, if still difficult, goal, in which case outcomes are judged as better or worse, or good or bad.

Wicked Problems (Explained)

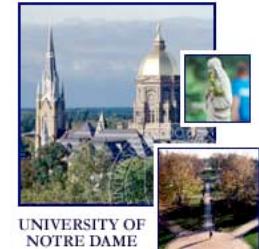


- π **Wicked problems cannot be tested definitively or immediately.**
Rigorous experimentation is not possible, it's impossible to test all possible solutions, and those solutions and their consequences of those solutions play out over time.

- π **Every implemented solution to a wicked problem has consequences.**
Every solution is unique, has multiple, often unknowable, consequences, and cannot be reversed nor reapplied. Each solution offers a 'one-shot' attempt.

- π **Wicked problems do not have a well-described set of potential solutions.**
Possible solutions are not enumerable, and their acceptability varies amongst stakeholders. The decision as to when sufficient potential solutions have emerged and which should be pursued is a political judgment.

Wicked Problems (Explained)



π **Every wicked problem is unique.**

There are no ‘classes’ of solutions that can be applied to a specific case – templates do not apply.

π **Every wicked problem can be considered a symptom of another problem.**

Wicked problems interlock and overlap and change over time. Rittel and Weber recommend that the problem at hand should be settled upon at a high a level as possible.

π **The causes of a wicked problem can be explained in numerous ways.**

Each stakeholder will have their own perspective on how the problem emerged and on its solution, and those perspectives will change over time.

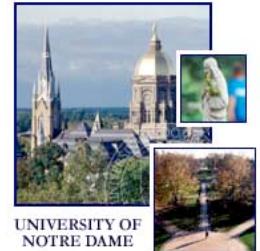
π **The planner, or designer, has no right to be wrong.**

A scientist is expected to formulate hypothesis, which may or may not be supportable by evidence. A designer doesn’t have such a luxury, they are expected to get things right.



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CAS Challenges

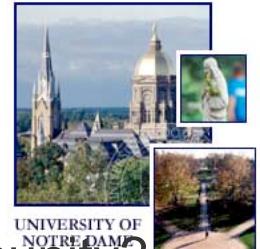


- π *Are Computational Models Predictive Under Uncertainty?*
- π In scientific computing, simulation credibility requires:
 - The fidelity of a model's predictions to empirical data (verification)
 - The degree to which the model is robust under uncertainty
 - The accuracy of the model in predicting phenomena in regions where experiments haven't been conducted
- π Main tradeoffs:
 - High fidelity models may be less robust to uncertainty
 - Models more robust under uncertainty may be less consistent in their predictions



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CAS Challenges



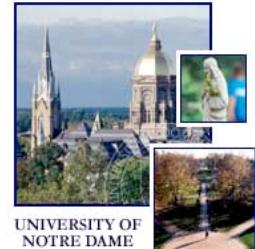
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- π Can we develop computation models as tools for a user community?
- π Consider computational models as tools like a hammer or a screwdriver:
 - Don't need to know a lot about their construction to use them
- π Scientific models
 - Require the user to know a lot about the guts before they can be used productively
 - Have complex structures where knowledge may be represented in multiple ways
 - Interpreting the model's output in a decision environment w/ significant consequences requires considerable cognitive familiarity with the model *and* the domain



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CAS Challenges



- π Can we trust the output of computational models over human judgment?
 - Models represent the current knowledge of a domain and problem space
 - Users may be wary of computational technologies that promise prediction, but whose workings they don't understand
 - Verification and validation require a considerable research investment in the code
- π Human judgment will always be an irreducible component of complex decision making
 - Computational models will not eliminate this role (anytime soon)

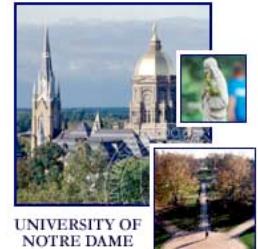
When a distinguished but elderly scientist states that something is possible, he is almost certainly right. When he states that something is impossible, he is very probably wrong.

—Arthur C. Clarke, *Report on Planet Three*



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CAS Challenges



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- π CAS is still an emerging discipline, but one that is mature in some areas
- π Most systematic studies of human behavior that follow the scientific model of research have analyzed numbers:
 - But, most human knowledge is represented in natural language in textual form
 - How to extract the relevant data in order to utilize it?
- π Are numerically-based simulations the best way of studying human behavior and interactions in different social milieu?
- π How can we best exploit object-oriented modeling (OOM) and OOP (programming) simulation for modeling social systems and processes?
- π Could OOM provide social science what the calculus provided physics?