Introduction to complex systems and agent based modeling

René Doursat, Mark Read, José Halloy
What are Complex Systems?

• *From “few” to “many” agents, from “simple” to “sophisticated” behavior*
What are complex systems?

- Few agents, “simple” emergent behavior
  
  → ex: two-body problem

  ✓ fully solvable and **regular** trajectories for inverse-square force laws (e.g., gravitational or electrostatic)

\[
\begin{align*}
F_{12}(x_1, x_2) &= m_1 \ddot{x}_1 \\
F_{21}(x_1, x_2) &= m_2 \ddot{x}_2
\end{align*}
\]

*(Equation 1)*

*(Equation 2)*
What are complex systems?

- Few agents, complex emergent behavior
  - ex: three-body problem
  - generally no exact mathematical solution (even in “restricted” case $m_1 \ll m_2 \approx m_3$): must be solved numerically $\rightarrow$ chaotic trajectories
What are complex systems?

- Few agents, complex emergent behavior
  - ex: more chaos (baker’s/horseshoe maps, logistic map, etc.)
  - chaos generally means a bounded, deterministic process that is aperiodic and sensitive on initial conditions → small fluctuations create large variations (“butterfly effect”)
  - even one-variable iterative functions: $x_{n+1} = f(x_n)$ can be "complex"
What are complex systems?

- Many agents, simple rules, “simple” emergent behavior
  - ex: crystal and gas (covalent bonds or electrostatic forces)
  - either highly ordered, **regular** states (crystal)
  - or disordered, random, statistically **homogeneous** states (gas):
    a few global variables (P, V, T) suffice to describe the system
What are complex systems?

- Many agents, simple rules, complex emergent behavior
  - ex: cellular automata, pattern formation, swarm intelligence (insect colonies, neural networks), complex networks, spatial communities
- the “clichés” of complex systems: a major part of this course and NetLogo models

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What are complex systems?

- Many agents, complicated rules, complex emergent behavior
  - natural ex: organisms (cells), societies (individuals + techniques)
  - agent rules become more “complicated”, e.g., heterogeneous depending on the element’s type and/or position in the system
  - behavior is also complex but, paradoxically, can become more controllable, e.g., reproducible and programmable

- termite mounds
- companies
- techno-networks
- cities
What are complex systems?

- Many agents, complicated rules, “deterministic” behavior

→ classical engineering: electronics, machinery, aviation, civil construction

- artifacts composed of a immense number of parts

- yet still designed globally to behave in a limited and predictable (reliable, controllable) number of ways — "I don’t want my aircraft to be creatively emergent in mid-air"

- not "complex" systems in the sense of:
  - little decentralization
  - no emergence
  - no self-organization
What are complex systems?

- Many agents, complicated rules, **“centralized”** behavior
  - spectators, orchestras, military, administrations
  - people reacting similarly and/or simultaneously to cues/orders coming from a **central cause**: event, leader, plan
  - hardly **"complex" systems**: little decentralization, little emergence, little self-organization
### Recap: complex systems in this course

<table>
<thead>
<tr>
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<th>Local Rules</th>
<th>Emergent Behavior</th>
<th>A &quot;Complex System&quot;?</th>
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<td>structured morphogenesis</td>
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<td>machines, crowds with leaders</td>
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## What are complex systems?

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A Complex Systems Sampler

- Observing & understanding (modeling) “natural” complex systems around us
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Physical pattern formation: Convection cells

- Rayleigh-Bénard convection cells in liquid heated uniformly from below (Scott Camazine, http://www.scottcamazine.com)
- Convection cells in liquid (detail) (Manuel Velarde, Universidad Complutense, Madrid)
- Sand dunes (Scott Camazine, http://www.scottcamazine.com)
- Solar magnetoconvection (Steven R. Lantz, Cornell Theory Center, NY)
- Hexagonal arrangement of sand dunes (Solé and Goodwin, “Signs of Life”, Perseus Books)

> thermal convection, due to temperature gradients, creates stripes and tilings at multiple scales, from tea cups to geo- and astrophysics.

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Biological pattern formation: Animal colors

Mammal fur, seashells, and insect wings
(Scott Camazine, http://www.scottcamazine.com)

NetLogo fur coat simulation, after David Young’s model of fur spots and stripes
(Michael Frame & Benoit Mandelbrot, Yale University)

animal patterns (for warning, mimicry, attraction) can be caused by pigment cells trying to copy their nearest neighbors but differentiating from farther cells

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Spatiotemporal synchronization: Neural networks

- The brain constantly generates patterns of activity ("the mind")
- They emerge from 100 billion neurons that exchange electrical signals via a dense network of contacts

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Swarm intelligence: Insect colonies (ant trails, termite mounds)

WHAT?

Termite mound
(J. McLaughlin, Penn State University)

http://cas.bellarmine.edu/tietjen/TermiteMound%20CS.gif

Harvester ant
(Deborah Gordon, Stanford University)

HOW?

ants form trails by following and reinforcing each other’s pheromone path

Termite stigmergy
(after Paul Grassé, from Solé and Good “Signs of Life”, Perseus Books)

termite colonies build complex mounds by “stigmergy”
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Collective motion: flocking, schooling, herding

WHAT?

Fish school
(Eric T. Schultz, University of Connecticut)

Separation, alignment and cohesion

• coordinated collective movement of dozens or thousands of individuals
  (to confuse predators, close in on prey, improve motion efficiency)
• each individual adjusts its position, orientation and speed according to its nearest neighbors

HOW?

Bison herd
(Center for Bison Studies, Montana State University, Bozeman)
Social biological complex systems: a model for autonomic computing

- Societies are multi-agents systems that process information, solve problems, make decisions, are factories and fortresses.

- These systems in which the units are mixed with the environment exhibit organizational structures that are functional, robust and adaptive.

- Well known experimental and theoretical examples are found in animal societies which are in essence similar to artificial systems in IT!

- Societies offer:
  - A complete blend of individual capacities and collective levels of intelligence and complexity;
  - A wide spectrum of size, physical constraints, …;
  - A wide spectrum of sharing of costs and benefits among members.
What kind of social structure?

Human centered problem-solving is based on the “Knowledge” of a “central unit” that makes decisions after collecting and processing all necessary information.

Workers

Queen

Where is THE BOSS?
Path choices and traffic flow regulation by ant colonies

Optimal traffic organization in ants under crowded conditions

Audrey Dussutour\textsuperscript{1,2}, Vincent Feuvray\textsuperscript{1,2}, Nick Mahon\textsuperscript{1,2} & Jean-Louis Deneubourg\textsuperscript{1,2}  

\textit{Nature} | Vol 428 | 4 March 2004

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Trails and U-turns in the Selection of a Path by the Ant \textit{Lasius niger}

R. Beckers, J. L. Deneubourg and S. Goss

Feedbacks during collective behavior

Cross-inhibition between trails

Crowding
Food depletion...

Negative feedback
Positive feedback

Loaded ant
Unloaded ant
Food

P1
P2
Trail reinforcement

Filling of food reserve
Limited number of potential recruits...
Self-organization defined by mechanism

Group of interacting agents

Stochastic behavior

Network of social & environmental feedbacks

Exploration of solution space

Collective pattern

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By emergent behaviour we mean a collective behaviour that is not explicitly programmed in each individual but emerge at the level of the group from the numerous interactions between these individuals that only follow local rules (no global map, no global representation) based on incomplete information.
Concepts

- Randomness

Individual actions include a level of *intrinsic randomness*. An action is never certain but has an intrinsic probability of occurring. The behaviour of each individual becomes then less predictable. The predictability of a system depends also on the level of description and the type of measures done. Randomness and fluctuations play an important role in allowing the system to find optimal solutions. In some cases, there is even an optimal level of noise that contributes to the discovery of optimal solutions. This noise is either at the level of the individuals or the interactions. It can be controlled in artificial systems and modulated in living systems.
Concepts

• Predictability

The global outcome of population presenting emergent behaviour is certain in well characterized systems. For instance, the result of emergent collective foraging in ant colonies is certain and efficient. Ants do bring food home or they simply die! Because often the system present multiple possible states coexisting for the same conditions, the specific solutions that accomplish the global behaviour at the level of the group are statistically predictable. For instance the optimal solution to solve a problem is chosen in 85% of the cases while a less optimal solution is selected in 15% of the cases. Nevertheless, the problem is solved in 100% of the cases! The discussion is then shifted towards knowing if 15% of suboptimal behaviour is acceptable and not if the global outcome is predictable.
Some features of self-organized social systems

• Problems are collectively solved in real time (no “out of the action” analysis) through the simple behaviour of individual sub-units, which interact with each other and with the environment.

• Dynamical systems with a large number of events: it does not necessarily mean a large number of individuals.

• At the collective level: a complexity/diversity of responses based on individual action relaying on incomplete information.

• Biological systems are not fully self-organised. Other social organizations are at work in biological systems like: templates, leadership & collection of specialists, sharing external signals.
Self-organization shown experimentally

Identified experimentally in natural systems: physical-chemistry & biology

- Is there a limited number of so generic rules are at work in biological systems (from the cellular level to animal societies, including plants) and produce optimal emergent collective patterns?

- What are these generic rules and their building blocks? What is the relevant level of description?

- What kind of patterns can be produced?

- Contrary to physical-chemistry, in biology we study the functionality of these pattern: functional self-organization.
Take-away message

The *purpose* of the individual behavioral pattern is not found at the individual but at the collective level. The mechanism is at the individual level taking into account the interactions; the purpose lies at the collective level.
Take-away message

In order to produce collective intelligence the systems must present *some nonlinear properties* coupled with positive or negative feedback mechanisms. One of the main roles of a positive feedback is to amplify random fluctuations to obtain a fast, nonlinear response of the system. To put it simply, innovation or efficient solutions are discovered by random fluctuations and selected by non-linear positive feedbacks.
Randomness is an essential counterintuitive ingredient because in a classical engineering approach it is considered as a nuisance. In the context of collective intelligence, individual actions include a level of *intrinsic randomness*. Like moving randomly or behaving in a probabilistic way. The behavior of each individual becomes then less predictable or even unpredictable. Nevertheless, collective intelligence can be predicted with accuracy or even produced systematically in artificial systems.
Take-away message

Distributing the team within the environment of the problem to be solved and introducing these positive feed-backs interactions between the units allows the amplification of localized information found by one or a few of the units. Thus, thanks to this type of coordination, the team reaction to these local signals is the solution to the problem. While no individual is aware of all the possible alternatives, and no individual possess an explicitly programmed solution, all together they reach an unconscious decision.
Take-away message

• The modeling framework briefly presented here does not mean that the individuals are necessarily simple. This is a common misunderstanding of this modeling framework. Even insects are sophisticated animals that have capabilities way beyond any available technology. The emergence of such collective problem solving in animal population is also based on sophisticated individual capabilities.

• However, while reviewing the hypothesis underlying such models, we notice that none of them is specific to animal species or even biology. Any system, including artificial ones, that fulfills these hypotheses will produce such emergent cooperative behavior.
The Immune System

- Collection of organs and vast numbers of cells responsible for maintaining your health
- Includes fighting bacteria, viruses, fungi
Immune System Function

- Recognizes and attacks only what is dangerous
- Bacteria in the gut not destroyed
- How does the immune system know to attack the harmful, and not the *self*?
- How does autoimmunity manifest?
- *... and why do most people not get sick when there are autoimmune cells in all of us?*
Emergent Immune Responses

• Immune system (IS) capable of carrying out many kinds of response
  – What is required to kill bacteria is different from what is required to kill a virus, which is different from what is required to remove waste in a healthy tissue
• The IS emerges from the actions of many different cell types: no one cell (or even type) is solely responsible for determining a response
• Cells communicate: directly through receptor-receptor interactions, and indirectly through secretion of proteins (stigmergy)
Immune system operation

- Response that emerges is dependent on many feedbacks between cells and tissues, across many compartments
  - Positive reinforcements to support helpful contributions
  - Negative feedbacks to prevent potentially harmful actions

E.g.
1) Tissue harmed by bacteria signals to immune cells that damage is taking place.
2) Immune cells sample local environment, consuming bacteria, showing samples to other cells that culminate in a response.
3) IS cells recognize and regulate other IS cells, and prevent excessive responses that are harmful to tissues

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Pathogenic escape and IS self-regulation

• Fighting pathogens is hard: evolutionary pressure to escape immune response
  – Common cold virus evolves very quickly, IS struggles to keep up
  – TB has protective capsule to avoid IS
  – Some pathogens live inside host cells to avoid detection
  – Pathogens that mimic healthy tissues

• IS continually generates new cells that recognize all sorts of structures
  – … some of which compose the host

• How does IS kill the harmful, and protect the host?
Killing the dangerous, protecting the host

- IS heavily populated with cells that recognize pathogens, body’s own tissues, and each other
- Many signals are integrated across many cell populations to direct the immune response
  - Tissues suppress reactions to themselves when no damage occurring (no pathogen present)
  - Tissues inform IS when damage occurs
  - IS associates harm to tissues with contents of tissue
  - IS self-regulates to prevent over-response
Immune System Awareness

• Immune system monitors itself, what it is doing, and whether that is causing harm or not
• It is *aware* of its own actions, and their consequences
• Based on this, it can change what it is doing
• This awareness is…
  – Distributed: cells & organs throughout the body.
  – Decentralized and self-organizing: No one cell/organ dictates actions
  – Flexible: response can change over time
A Complex Systems Sampler

Social networks and human organizations at multiple levels

- enterprise
- urban systems
- cellular automata model
- global networks
- national grids

**HOW?**
- SimCity
  [http://simcitysocieties.ea.com](http://simcitysocieties.ea.com)
- NSFNet Internet
  [w2.eff.org](http://w2.eff.org)
- NetLogo urban sprawl simulation
- “scale-free” network model

**WHAT?**

- NetLogo preferential attachment simulation

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All agent types: molecules, cells, animals, humans & tech

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Categories of complex systems by range of interactions

- 2D, 3D spatial range
- Non-spatial, hybrid range

- Biological patterns
- Physical patterns
- Living cell
- The brain
- Organisms
- Ant trails
- Termite mounds
- Animal flocks
- Cities, populations
- Internet, Web
- Markets, economy
- Social networks

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Natural and human-caused categories of complex systems

... yet, even human-caused systems are “natural” in the sense of their unplanned, spontaneous emergence

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Architectured natural complex systems (without architects)

- the brain
- organisms
- ant trails
- termite mounds
- animal flocks
- cities, populations
- social networks
- markets, economy
- Internet, Web
- physical patterns
- biological patterns
- living cell

➢ biology strikingly demonstrates the possibility of combining pure self-organization and elaborate architecture

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awareness
SELF-AWARENESS IN AUTONOMIC SYSTEMS

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Emergence on multiple levels of self-organization in complex systems:

a) a large number of elementary agents interacting locally

b) simple individual behaviors creating a complex emergent collective behavior

c) decentralized dynamics: no master blueprint or grand architect
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From genotype to phenotype, via development
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➢ From cells to pattern formation, via reaction-diffusion
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- From social insects to swarm intelligence, via stigmergy
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➢ From birds to collective motion, via flocking

- ecosystems
- groups, societies
- organisms
- cells
- macromolecules
- atoms, metabolites

flocks

flocking

birds

NetLogo

“Flock”

separation
alignment
cohesion

NetLogo 

Flock

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From neurons to brain, via neural development
Common Properties of Complex Systems

- Emergence, self-organization
- Positive feedback, decentralization
- Between simple and disordered
- “More is different”, phase transitions
- Adaptation & evolution
Common Properties of Complex Systems

- **Emergence**
  - ✓ the system has properties that the elements do not have
  - ✓ these properties cannot be easily inferred or deduced
  - ✓ different properties can emerge from the same elements

- **Self-organization**
  - ✓ “order” of the system increases without external intervention
  - ✓ originates purely from interactions among the agents (possibly via cues in the environment)

- **Counter-examples of emergence without self-organization**
  - ✓ ex: well-informed leader (orchestra conductor, military officer)
  - ✓ ex: global plan (construction area), full instructions (program)
Common Properties of Complex Systems

Positive feedback, circularity
- creation of structure by amplification of fluctuations
  (homogeneity is unstable)
  - ex: termites bring pellets of soil where there is a heap of soil
  - ex: cars speed up when there are fast cars in front of them
  - ex: the media talk about what is currently talked about in the media

Decentralization
- the “invisible hand”: order without a leader
  - ex: the queen ant is not a manager
  - ex: the first bird in a V-shaped flock is not a leader
- distribution: each agent carry a small piece of the global information
- ignorance: agents don’t have explicit group-level knowledge/goals
- parallelism: agents act simultaneously
NOTEDecentralized processes are far more abundant than leader-guided processes, in nature and human societies

... and yet, the notion of decentralization is still counterintuitive

- many decentralized phenomena are still poorly understood
- a “leader-less” or “designer-less” explanation still meets with resistance
- this is due to a strong human perceptual bias toward an identifiable source or primary cause
key concepts ("buzzwords") expressing different facets of CS

- some have different definitions across disciplines; no global agreement
- others have a clearer meaning but different weights in “making” CS
- terms overlapping but not equivalent; yet, often grouped or interchanged

Adaptation
Positive feedback
Far from equilibrium
Phase transitions
"More is different"

Between simple and disordered
Self-organization
Decentralization
Emergence
Adaptation

Common Properties of Complex Systems

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Common Properties of Complex Systems

Emergence

✓ the system has properties that the elements do not have
  - ex: microscopic units form macroscopic patterns (convection rolls, spiral waves, stripes, spots)
  - ex: “ignorant” individuals make intelligent collective decisions (insect colonies, neurons, market traders)

✓ these properties cannot be easily inferred or deduced
  - ex: liquid water or ice emerging from H₂O molecules
  - ex: cognition and consciousness emerging from neurons

✓ different properties can emerge from the same elements/rules
  - ex: the same molecules of water combine to form liquid or ice crystals
  - ex: the same cellular automaton rules change behavior from initial state

✓ global properties can constitute local rules at a higher level:
  jumping from level to level through emergence
Common Properties of Complex Systems

Self-organization

✓ the organization or “order” of the system increases internally without external intervention
  - ex: aggregating processes (slime mold, pigmentation spots, termite heaps, flocks, etc.)

✓ order can be quantified using an “order parameter”
  - ex: cluster rate in aggregation
  - ex: long-range spatiotemporal correlations (spiral waves, synchrony)

✓ crucial to the notion of self-organization are the interactions among elements (vs. interaction with an external cause)
  - either directly: element ↔ element
  - or indirectly: element ↔ environment ↔ element (“stigmergy” in social insects)
Common Properties of Complex Systems

Emergence & self-organization

✓ counter-examples of emergence without self-organization
  ▪ ex: well-informed leader (orchestra conductor, military officer)
  ▪ ex: global plan (construction area), full instructions (orchestra)

✓ immergence: emergent structure feeds back to the elements
  ▪ ex: market influences buyers, traffic jam influences drivers

Chris Langton’s view of emergence in complex systems
(from “Complexity”, Roger Lewin, University of Chicago Press)
Common Properties of Complex Systems

Positive feedback

- positive feedback, circularity
  - ex: ants bring more pheromone where there is pheromone
  - ex: termites bring pellets of soil where there is a heap of soil
  - ex: pigmented cells differentiate next to other pigmented cells
  - ex: fireflies want to synchronize with the swarm’s flashes
  - ex: cars speed up where there are fast cars in front of them
  - ex: traders prefer buying stock that goes up
  - ex: the media talk about what is currently talked about in the media

→ amplification of fluctuations (nonlinearity)

→ instability of initially homogeneous state

→ broken symmetry

→ creation of structure
Common Properties of Complex Systems

Decentralization

✓ order without a leader
  - ex: the central amoeba in spiral waves is *not* a pacemaker
  - ex: the queen ant is *not* a manager
  - ex: the first bird in a V-shaped flock is *not* a leader

✓ the “invisible hand”
  - distribution: each element carry a small piece of the global information
  - ignorance: elements don’t have explicit knowledge or goals about the group
  - parallelism: elements act simultaneously

✓ decentralized processes are far more abundant than leader-guided processes, in nature and human societies

✓ ... and yet, the notion of decentralization is still counterintuitive
  - many decentralized phenomena are still poorly understood
  - a “leader-less” or “designer-less” explanation still meets with resistance
    → mostly due to human perceptual bias toward an identifiable source or primary cause
Common Properties of Complex Systems

Between simple and disordered

✓ Warren Weaver’s 1948 classification of scientific activity
  1. Problems of simplicity 1- to few-variable problems of the 17th, 18th and 19th centuries: Newtonian mechanics, electricity, chemistry, etc.
  2. Problems of disorganized complexity million- and billion-variable problems of the 20th century: statistical mechanics (gas, fluid, solid), probability theory, theory of information, etc.
  3. Problems of organized complexity (“middle region”) dozens or hundreds of interrelated variables [21st century problems]: biology, medicine, psychology, economics, social science, etc.

✓ the billiards table analogy (from S. Johnson’s book “Emergence”)
  1. a few balls: individual trajectories from velocities, angles, friction
  2. a million balls: only broad statistical trends (average path, pressure)
  3. a hundred motorized balls obeying simple rules and self-arranging → ??

✓ another classification: Wolfram’s or Langton’s 4 classes of cellular automata
Common Properties of Complex Systems

“More is different”, phase transitions

✓ Philip W. Anderson’s 1972 slogan “More is different”
  - criticism of the reductionist/constructionist hard line: “after discovering the fundamental laws, it is just a matter of reconstructing from them”
  - ...however, particle physics does not help solid state physics or biology!
  - reconstructionism crashes on the cliffs of scale and complexity
  - hierarchy levels of science show qualitative leaps (new properties)
  - psychology is not just applied biology, biology is not applied chemistry
  - ...yet again, this does not imply any unknown external or mysterious force; only a fundamental limitation in our analytical tools

✓ notion of “critical mass”
  - ex: need enough ants for a pheromone trail to form
  - ex: need enough chemical types for an autocatalytic set to appear

✓ phase transitions in parameter space
  - broken symmetries
  - most interesting: transition from randomness or chaos to order
Common Properties of Complex Systems

Decentralization vs. “more is different”?

✓ recap: decentralization (the “invisible hand”)
  ▪ no leader, no designer, no external organizing force that does not belong to the system
  ▪ the emergent properties entirely rely on the elements’ behavior and interactions among *themselves*

✓ recap: “more is different”
  ▪ ... but these properties cannot be *inferred* or *predicted* just by looking at the elements
  ▪ beyond a critical mass and across phase transition lines, the system exhibits *qualitatively new* behaviors

→ only an apparent paradox
  ▪ both aspects can, and actually do coexist in natural systems
  ▪ neither hard-line reductionism (“everything boils down to superstrings”)
  ▪ nor “vitalism” or intelligent design (“something else must intervene”)
Common Properties of Complex Systems

“Complexity”: an illusion?

✓ abundance of autonomous, emergent systems in the environment
  ▪ nature: geological patterns, biological cells, organisms, animal societies, ecosystems, etc.
  ▪ spontaneously emerging human-made super-structures: cities, markets, Internet, etc.

→ decentralized, unplanned systems are robust, efficient and constitute the overwhelming majority of system types
  ▪ it is our artificially centralized, planned engineered systems that are fragile, costly to build, and rare, as they require a higher intelligence to arise

✓ “complexity”, an artifact of our cognitive bias?
  ▪ because we are accustomed to the illusion of a central consciousness, we traditionally refer to decentralized systems as “complex”
  ▪ but in fact these systems might be simpler than our familiar engineered devices with their uniquely hierarchical and complicated arrangement

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Common Properties of Complex Systems

A vast archipelago

- Precursor and neighboring disciplines

- **complexity**: measuring the length to describe, time to build, or resources to run, a system
- **dynamics**: behavior and activity of a system over time
- **systems sciences**: holistic (non-reductionist) view on interacting parts
- **adaptation**: change in typical functional regime of a system
- **multitude, statistics**: large-scale properties of systems

- different families of disciplines **focus** on different aspects
- *(naturally, they intersect a lot: don’t take this taxonomy too seriously)*
Common Properties of Complex Systems

A vast archipelago

Precursor and neighboring disciplines

complexity: measuring the length to describe, time to build, or resources to run, a system
  - information theory (Shannon; entropy)
  - computational complexity (P, NP)
  - Turing machines & cellular automata

adaptation: change in typical functional regime of a system
  - evolutionary methods
  - genetic algorithms
  - machine learning

systems sciences: holistic (non-reductionist) view on interacting parts
  - systems theory (von Bertalanffy)
  - systems engineering (design)
  - cybernetics (Wiener; goals & feedback)
  - control theory (negative feedback)

→ Toward a unified “complex systems” science and engineering?

dynamics: behavior and activity of a system over time
  - nonlinear dynamics & chaos
  - stochastic processes
  - systems dynamics (macro variables)

multitude, statistics: large-scale properties of systems
  - graph theory & networks
  - statistical physics
  - agent-based modeling
  - distributed AI systems

Toward a unified “complex systems” science and engineering?
Common Properties of Complex Systems

- Sorry, there is no general “complex systems science” or “complexity theory”...
  - there are a lot of theories and results in related disciplines (“systems theory”, “computational complexity”, etc.), yet
    - such generic names often come from one researcher with one particular view
    - there is no unified viewpoint on **complex systems**, especially autonomous
    - in fact, there is not even any agreement on their definition
  - we are currently dealing with an intuitive set of criteria, more or less shared by researchers, but still hard to formalize and quantify:
    - complexity
    - emergence
    - self-organization
    - multitude / decentralization
    - adaptation, etc.
The Need for Computational Models
The Need for Computational Models

- **Existence of macro-equations for some dynamic systems**
  - we are typically interested in obtaining an explicit description or expression of the behavior of a whole system over time
  - in the case of dynamical systems, this means solving their evolution rules, traditionally a set of **differential equations** (DEs)
  - either **ordinary** (O)DEs of **macro-variables** in **well-mixed** systems
    - ex: in chemical kinetics, the law of mass action governing concentrations: 
      \[ \alpha A + \beta B \rightarrow \gamma C \] 
      described by 
      \[ \frac{d[A]}{dt} = -\alpha k [A]^\alpha [B]^\beta \]
    - ex: in economics, (simplistic) laws of gross domestic product (GDP) change: 
      \[ \frac{dG(t)}{dt} = \rho G(t) \]
  - or **partial** (P)DEs of **local variables** in **spatially extended** systems
    - ex: heat equation: 
      \[ \frac{\partial u}{\partial t} = \alpha \nabla^2 u \] 
    - wave equation: 
      \[ \frac{\partial^2 u}{\partial t^2} = c^2 \nabla^2 u \]
    - ex: Navier-Stokes in fluid dynamics, Maxwell in electromagnetism, etc.
The Need for Computational Models

- Existence of macro-equations and an analytical solution
  - in some cases, the explicit formulation of an exact solution can be found by calculus, i.e., the *symbolic manipulation of expressions*
    - ex: geometric GDP growth \( \Rightarrow \) exponential function
      \[
      \frac{dG(t)}{dt} = \rho \ G(t) \quad \Rightarrow \quad G(t) = G(0) \ e^{\rho \ t}
      \]
    - ex: heat equation \( \Rightarrow \) linear in 1D borders; widening Gaussian around Dirac
      \[
      \frac{\partial u}{\partial t} = \alpha \ \frac{\partial^2 u}{\partial^2 x} \quad \text{and} \quad u(x,0) = \delta(x) \quad \Rightarrow \quad u(x,t) = \frac{1}{\sqrt{4\pi kt}} \exp\left(-\frac{x^2}{4kt}\right)
      \]
  - calculus (or analysis) relies on known shortcuts in the world of mathematical "regularities", i.e., mostly the family of continuous, derivable and integrable functions that can be expressed symbolically
    - unfortunately, although vast, this family is in fact very small compared to the immense range of dynamical behaviors that natural complex systems can exhibit!
Small graphs of interactions can be mapped to a dynamical system

Given a positive integer $m$, we define a differentiable map $F: \mathbb{R}^m \rightarrow \mathbb{R}^m$ and the corresponding dynamical system:

$$\frac{dx}{dt} = F(x)$$

Where $x=(x_1(t), \ldots, x_m(t))$ is a trajectory in the $m$-dimensional Euclidean space.

The interaction graph $G(x)$ of $F$ at the point $x$ is the oriented graph with \{1,...,m\} as set of vertices and such that there is a positive (respectively negative) arrow from $j$ to $i$ if and only if the partial derivative:

$$\frac{\partial f_i}{\partial x_j}(x)$$

is positive (respectively negative). Each edge in $G(x)$ is thus oriented and endowed with a sign. The variable $x$ is viewed as the phase space location of the graph $G(x)$.

A circuit in the graph $G(x)$ is a sequence of distinct vertices $i_1, i_2, \ldots, i_k$ such that there is an edge from $i_{\alpha}$ to $i_{\alpha+1}$, with $1 \leq \alpha \leq k-1$, and from $i_k$ to $i_1$. The sign of a circuit is the product of the signs of it edges. A circuit is thus determined by a set of non zero coefficients in the jacobian matrix:

$$J(x) = \begin{pmatrix} \frac{\partial f_i}{\partial x_j}(x) \end{pmatrix}$$

which rows and columns are in cyclic permutation.
The Jacobian matrix allows predicting the existence of various type of attractor

TABLE I. Strictly speaking, this table is valid only for pure full-circuits. To what extent it also holds for nonzero values of the other elements of the Jacobian matrix, is described in Sec. IV B.

<table>
<thead>
<tr>
<th>Pure full-circuits in 2 variables</th>
<th>Eigenvalues</th>
<th>Steady state</th>
</tr>
</thead>
<tbody>
<tr>
<td>The 2-circuit</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive (−) or (+)</td>
<td>(+,−)</td>
<td>Saddle point</td>
</tr>
<tr>
<td>Negative (−) or (+)</td>
<td>complex</td>
<td>Center(^a)</td>
</tr>
<tr>
<td>The unions of two 1-circuits</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(−)</td>
<td>(−,−)</td>
<td>Stable ‘‘node’’</td>
</tr>
<tr>
<td>(−) or (+)</td>
<td>(+,−)</td>
<td>‘‘Saddle point’’</td>
</tr>
<tr>
<td>(+)</td>
<td>(+,+)</td>
<td>Unstable ‘‘node’’</td>
</tr>
</tbody>
</table>

\(^a\)If the diagonal elements are nonzero, the steady state is a focus, stable or unstable depending on the sign of the trace.

FIG. 8. \(\dot{x} = -x + z, \dot{y} = x - y, \dot{z} = -x^2 + y\), whose Jacobian matrix is \(\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ -2 & 0 & 1 \end{bmatrix}\). There is multistationarity (three steady states, a saddle point of type \(+/−−\), and two saddle points of type \(−/++/\)), in agreement with the presence of two full-circuits of opposite signs. There is a positive circuit responsible for multistationarity (from that viewpoint, the positive 1-circuit is dispensable) and a negative 2-circuit responsible for periodicity around the two external foci. For \(\epsilon \approx 0.49\), the dynamics is chaotic.

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The Jacobian matrix allows predicting the existence of various type of attractor

Here are four conjectures that can be made about the behaviour of a dynamical system as above:

**Conjecture 1.** (Thomas) The presence of a positive circuit (somewhere in phase space) is a necessary condition for multistationarity.

**Conjecture 2.** (Kaufman) Multistationarity requires either the presence of a variable nucleus or else the presence of two nuclei of opposite signs.

**Conjecture 3.** (Thomas) The presence of a negative circuit of length at least two (somewhere in phase space) is a necessary condition for stable periodicity.

**Conjecture 4.** (Thomas) A chaotic dynamics requires both a positive and a negative circuit.
The Need for Computational Models

- **Existence of macro-equations but no analytical solution**
  - when there is no symbolic resolution of an equation, *numerical analysis* involving algorithms (step-by-step recipes) can be used
  - it involves the discretization of space into cells, and time into steps

\[
\frac{\partial u}{\partial t} = \alpha \nabla^2 u \quad \text{by forward Euler}
\]

\[
\Delta u_{i,j} = \alpha (u_{i,j-1} + u_{i,j+1} + u_{i-1,j} + u_{i+1,j} - 4u_{i,j})
\]

NetLogo model: /Chemistry & Physics/Heat/Unverified/Heat Diffusion

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The Need for Computational Models

Absence of equations: where ODEs and PDEs break down

- systems that no macroscopic quantity suffices to explain (ODE)
  - no law of "concentration", "pressure", or "gross domestic product"
  - even if global metrics can be designed to give an indication about the system’s dynamical regimes, they rarely obey a given equation or law

- systems that require a non-Cartesian decomposition of space (PDE)
  - network of irregularly placed or mobile agents

- systems that contain heterogeneity
  - segmentation into different types of agents
  - at a fine grain, this would require a "patchwork" of regional equations (ex: embryo)

- systems that are dynamically adaptive
  - the topology and strength of the interactions depend on the short-term activity of the agents and long-term "fitness" of the system in its environment

ex: embryogenesis
The Need for Computational Models

ABM meets MAS: two (slightly) different perspectives

**CS science:** understand “natural” CS

→ Agent-Based Modeling (ABM)

**CS engineering:** design a new generation of “artificial” CS → Multi-Agent Systems (MAS)

✓ but again, don’t take this distinction too seriously! they overlap a lot
The Need for Computational Models

**ABM: the modeling perspective from CA & social science**

- **agent-based modeling** (ABM) arose from the need to model systems that were too complex for analytical descriptions.

- One origin: cellular automata (CA)
  - von Neumann self-replicating machines → Ulam’s “paper” abstraction into CAs → Conway’s *Game of Life*
  - Based on **grid** topology

- Other origins rooted in economics and social sciences
  - Related to “methodological individualism”
  - Mostly based on grid and **network** topologies

- Later: extended to ecology, biology and physics
  - Based on grid, network and 2D/3D **Euclidean** topologies

→ *the rise of fast computing made ABM a practical tool*
The Need for Computational Models

MAS: the engineering perspective from computer sci. & AI

- in software engineering, the need for clean architectures
  - historical trend: breaking up big monolithic code into layers, modules or objects that communicate via application programming interfaces (APIs)
  - this allows fixing, upgrading, or replacing parts without disturbing the rest
- in AI, the need for distribution (formerly “DAI”)
  - break up big systems into smaller units creating a decentralized computation: software/intelligent agents
- difference with object-oriented programming:
  - agents are “proactive” / autonomously threaded
- difference with distributed (operating) systems:
  - agents don’t appear transparently as one coherent system

→ the rise of pervasive networking made distributed systems both a necessity and a practical technology
The Need for Computational Models

- An agent in complex systems modeling:
  - a (small) program deemed “local” or “autonomous” because it has
    - its own scheduling (execution process or thread)
    - its own memory (data encapsulation)
    - ... generally simulated in a virtual machine
  - this agent-level program can consist of
    - a set of dynamical equations (“reactive”) at the microscopic level
    - a set of logical rules (AI)... or a mix of both
  - peer-to-peer interactions among agents under different topologies
The Need for Computational Models

➤ Agent virtual machines or “platforms”

✓ just like there are various middleware-componentware frameworks...

✓ ... there are also ABM platforms, e.g., NetLogo, Swarm, or Repast
The Need for Computational Models
The NetLogo Platform

✓ programmable modeling environment for simulating natural and social phenomena

- well suited for complex system modeling that evolves over time
- hundreds or thousands of independent agents operating concurrently
- exploring the connection between the micro-level behavior of individuals and the macro-level patterns that emerge from the interaction of many individuals
The Need for Computational Models

The NetLogo Platform

- easy-to-use application development environment
  - opening simulations and playing with them
  - creating custom models: quickly testing hypotheses about self-organized systems
  - models library: large collection of pre-written simulations in natural and social sciences that can be used and modified
  - simple scripting language
  - user-friendly graphical interface
The Need for Computational Models

The NetLogo Platform

- **LOGO (Papert & Minsky, 1967)**
  - theory of education based on Piaget’s constructionism (“hands-on” creation and test of concepts)
  - simple language derived from LISP
  - turtle graphics and exploration of “microworlds”

- **StarLogo (Resnick, 1991), MacStarLogo, StarLogoT**
  - agent-based simulation language
  - exploring the behavior of decentralized systems through concurrent programming of 100s of turtles

- **NetLogo (Wilensky, 1999)**
  - further extending StarLogo (continuous turtle coordinates, cross-platform, networking, etc.)
  - most popular today (growing cooperative library of models)
The Need for Computational Models
The NetLogo Platform

✓ NetLogo is a 2-D world made of 3 kinds of agents:
  - *patches* – make up the background or “landscape”
  - *turtles* – move around on top of the patches
  - *the observer* – oversees everything going on in the world

Falsy examples of patch-only models

- B-Z reaction
- Fur

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The NetLogo Platform

- examples of turtle-only models
  - Flocking
  - Fireflies

- examples of patch-&-turtle models
  - Ants
  - Termites

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