

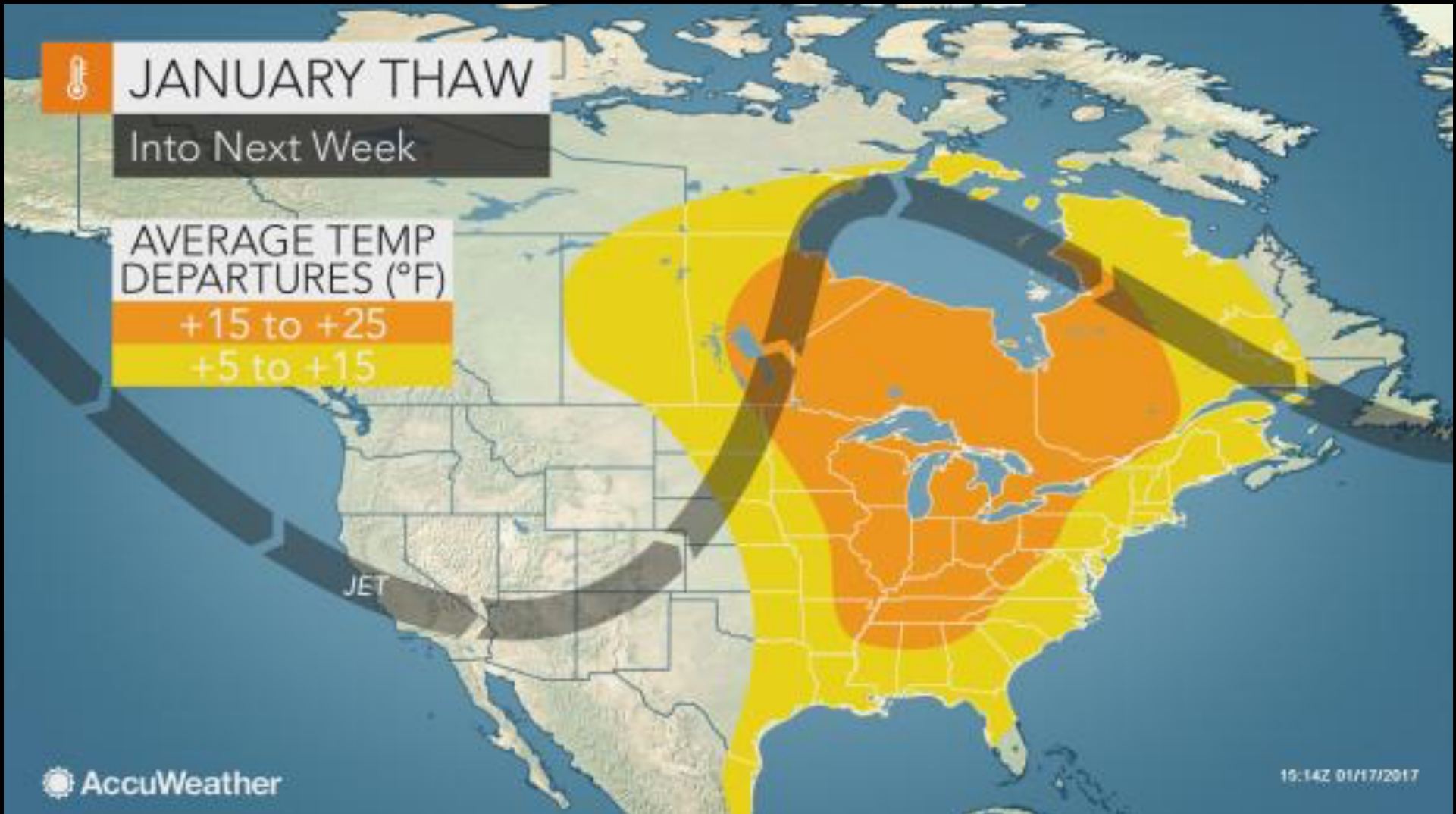
Complex Adaptive Systems

Lecture 1

Matthew Fricke

Course Website: cs.unm.edu/~mfricke

Weather (or where is the snow?)



Complex Adaptive Systems

Interactions

Emergence

Scale

Evolution and Learning

Complex Systems

Interactions

Systems composed of interacting components

Emergence

Scale

Evolution and Learning

Complex Systems

Interactions

Systems composed of interacting components

Emergence

Behavior emerges from interactions among components and between components and their environment

Scale

Evolution and Learning

Complex Systems

Interactions

Systems composed of interacting components

Emergence

Structure and behavior emerges from interactions among components and between components and their environment

Scale

Systems are nested and structure/behavior emerges at different scales

Evolution and Learning

Complex (Adaptive) Systems

Interactions

Systems composed of interacting components

Emergence

Structure and behavior emerges from interactions among components and between components and their environment

Scale

Systems are nested and structure/behavior emerges at different scales

Evolution and Learning

Systems are dynamic and adapt to internal and external conditions

Complex (Adaptive) Systems

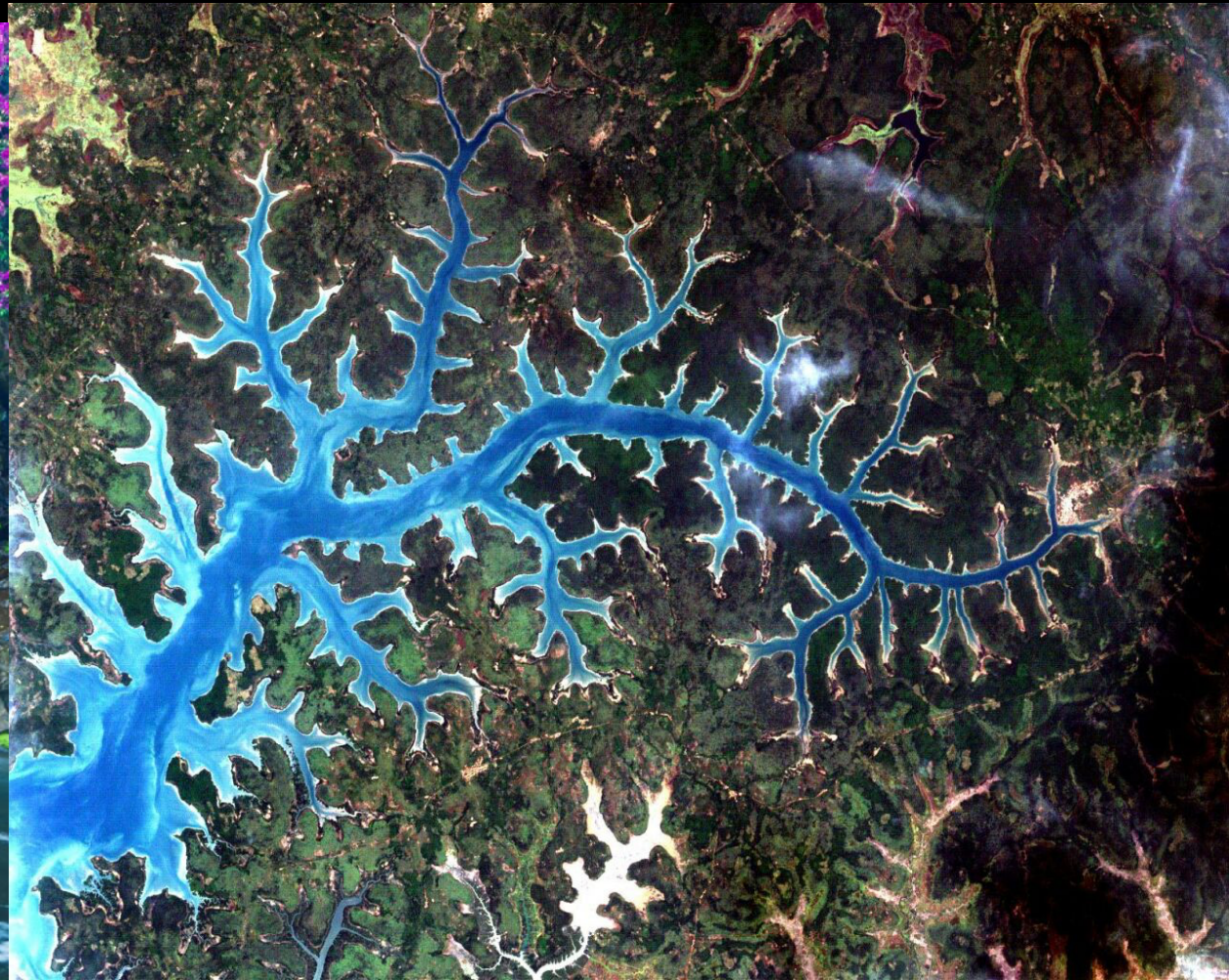
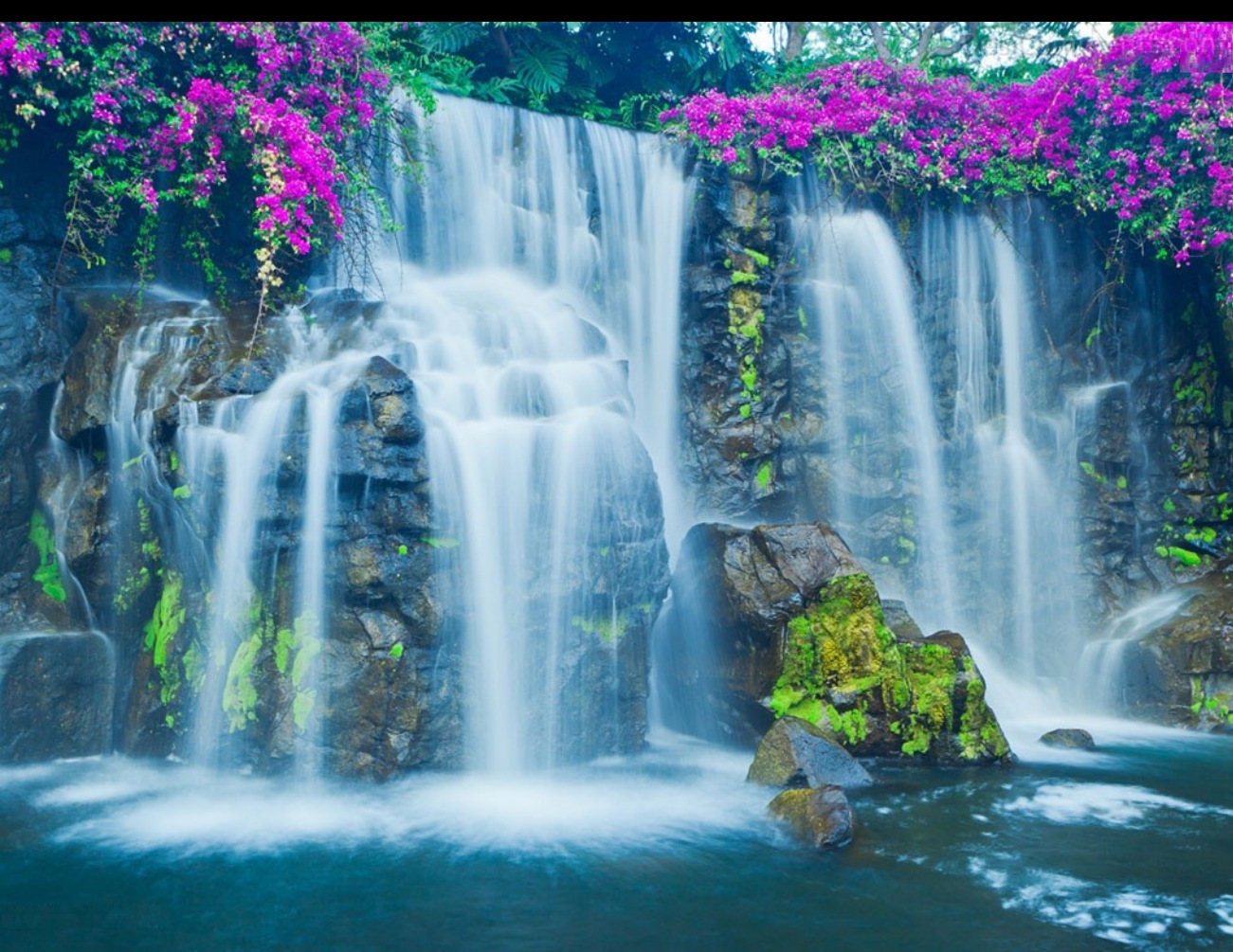
Unifying Idea

Between the world of order and the world of chaos
exist Complex Systems

Complex Systems have emergent properties.

Complex Adaptive Systems can exploit these emergent properties
in order to solve a problem.

A Complex System

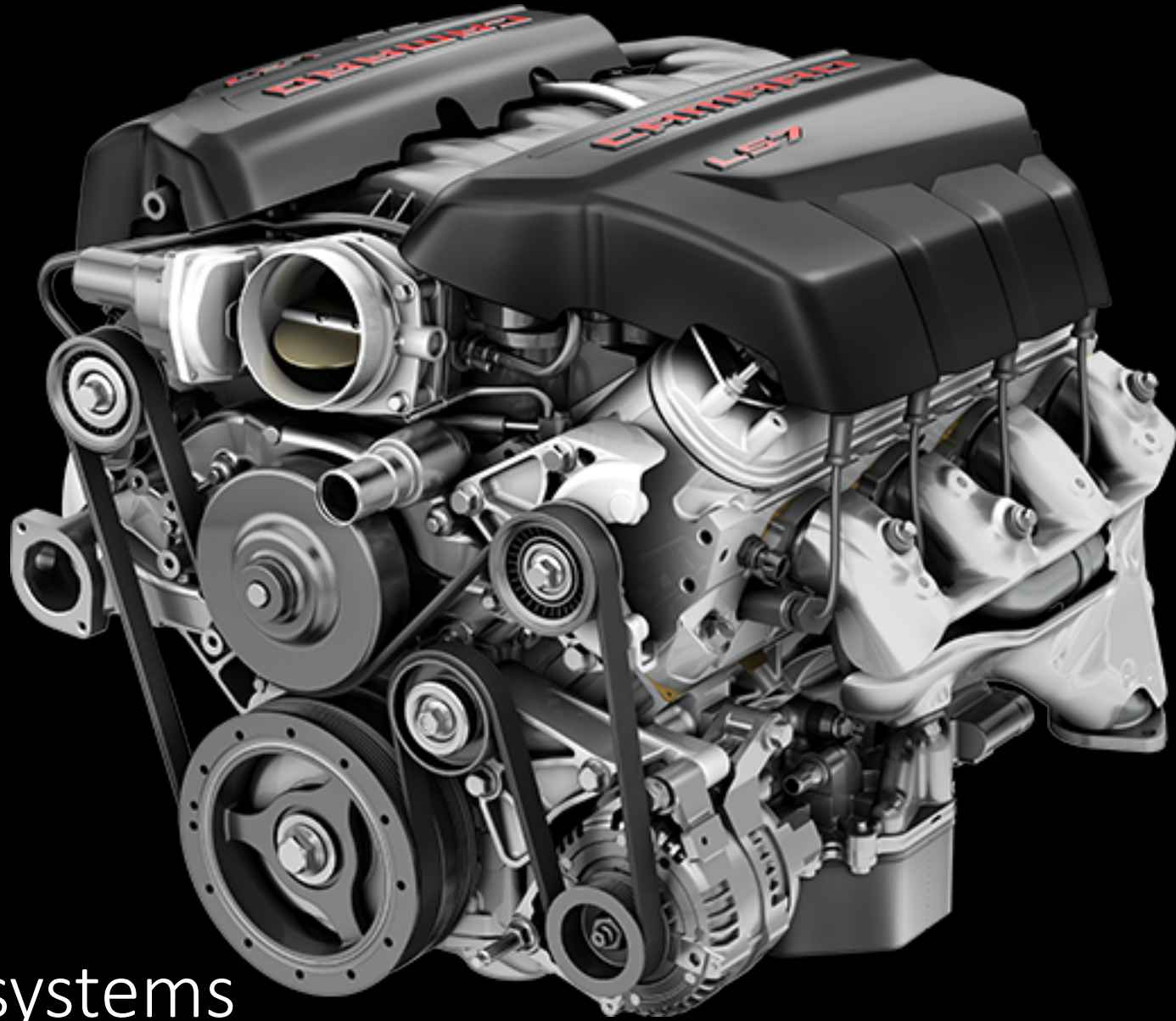


A Complicated System

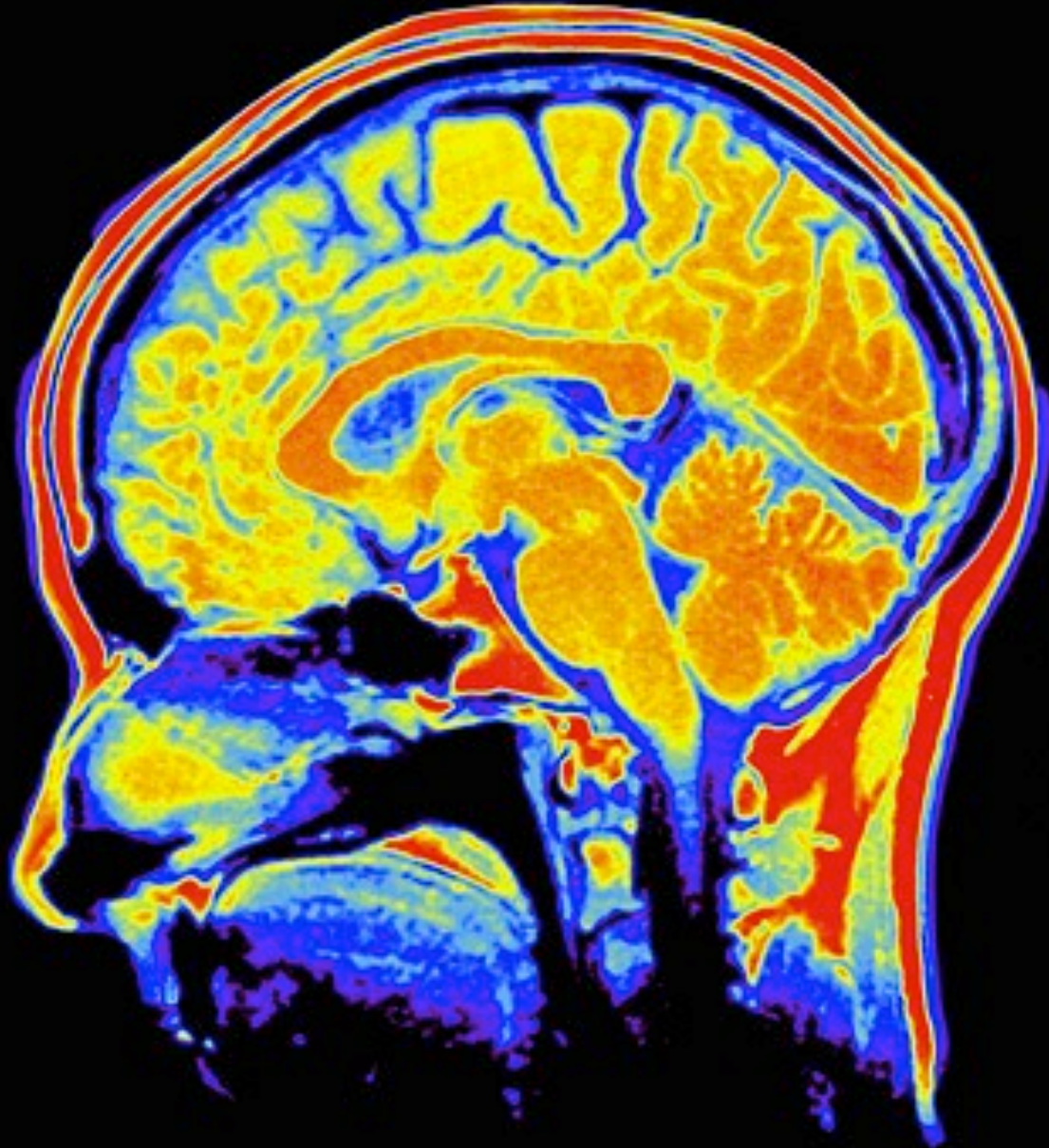
No emergent properties.

Remove one component and the whole stops working.

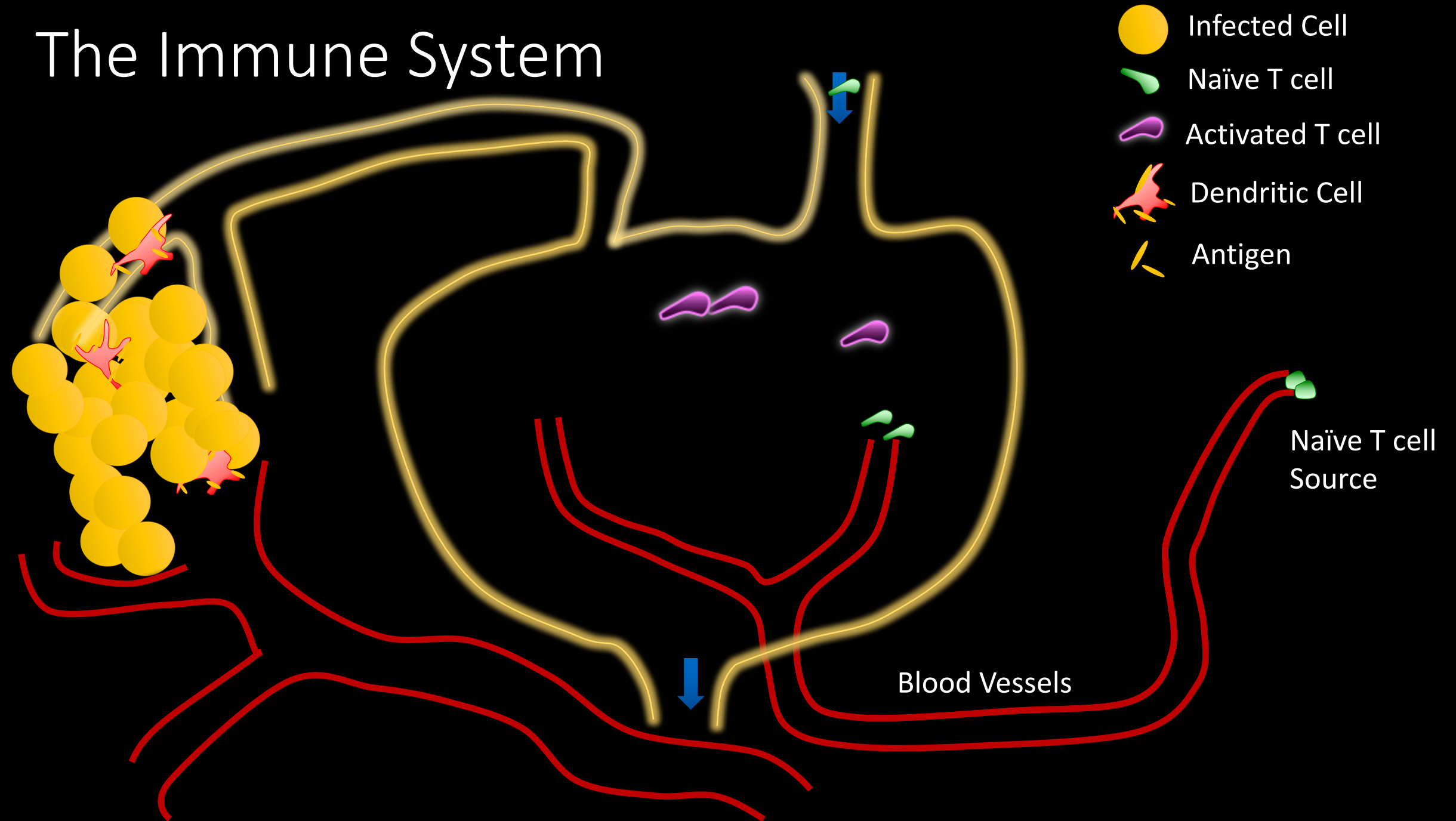
Complicated systems can be complex but not all complex systems are complicated.



Brains



The Immune System



Financial Markets and Economies



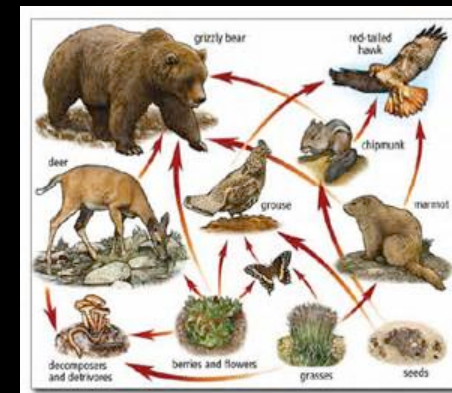
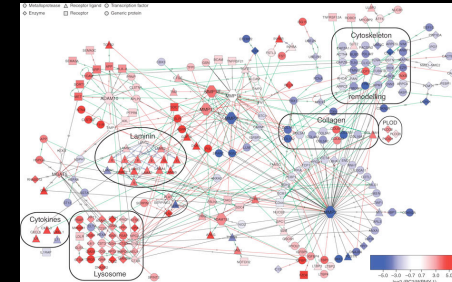
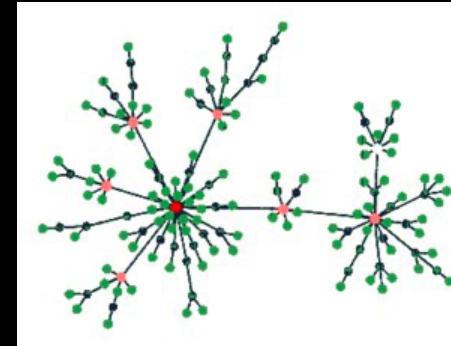
<http://selectusa.commerce.gov/industry-snapshots/financial-services-industry-united-states>



<http://www.atelier.net/en/trends/articles/harnessing-wisdom-crowds-help-play-financial-markets>

Networks

- Generic: Nodes and links
- Network structure
 - Degree of a node
 - Degree distribution
- Scale free networks
 - Same structure at all scales
 - Power law distribution
- How are they produced?
 - Preferential attachment
 - And other mechanisms



Cities

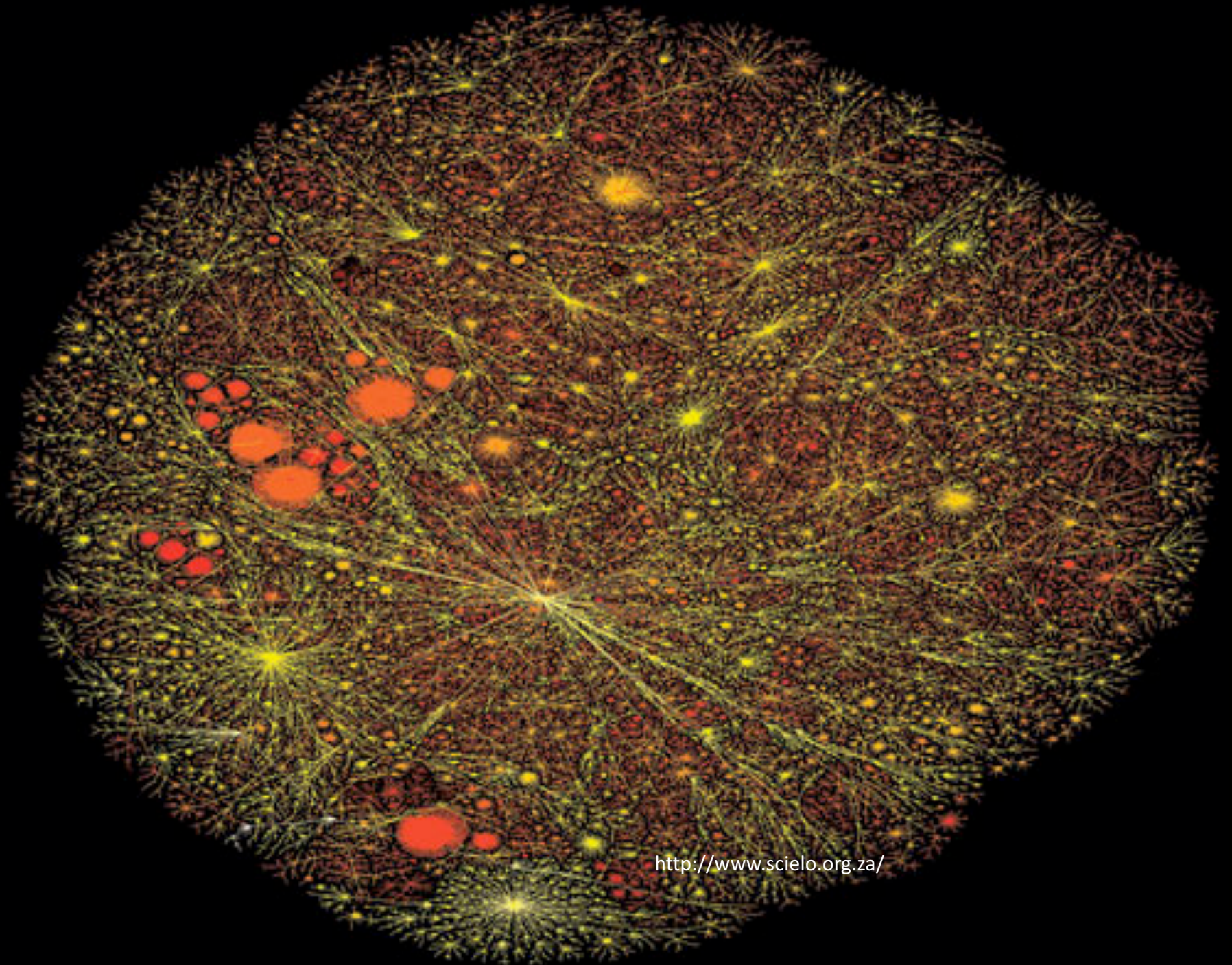








The Internet



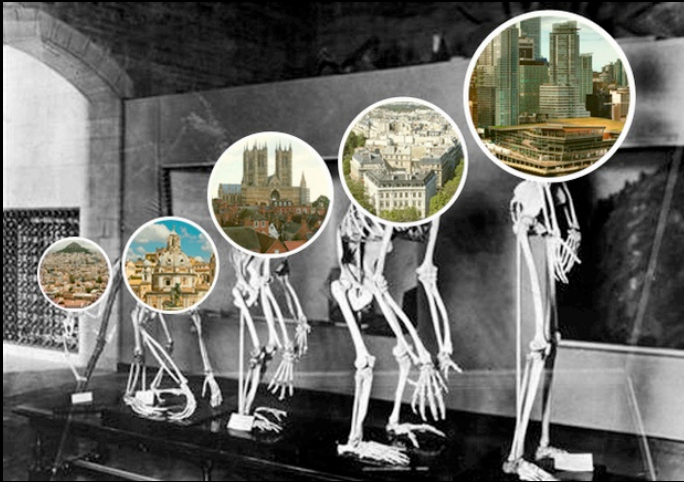
<http://www.scielo.org.za/>

Social Networks



<http://www.telegraph.co.uk/finance/businessclub/management-advice/8856162/Think-Tank-Making-social-media-sites-such-as-Facebook-and-Twitter-more-personal.html>

New Theories about Cities

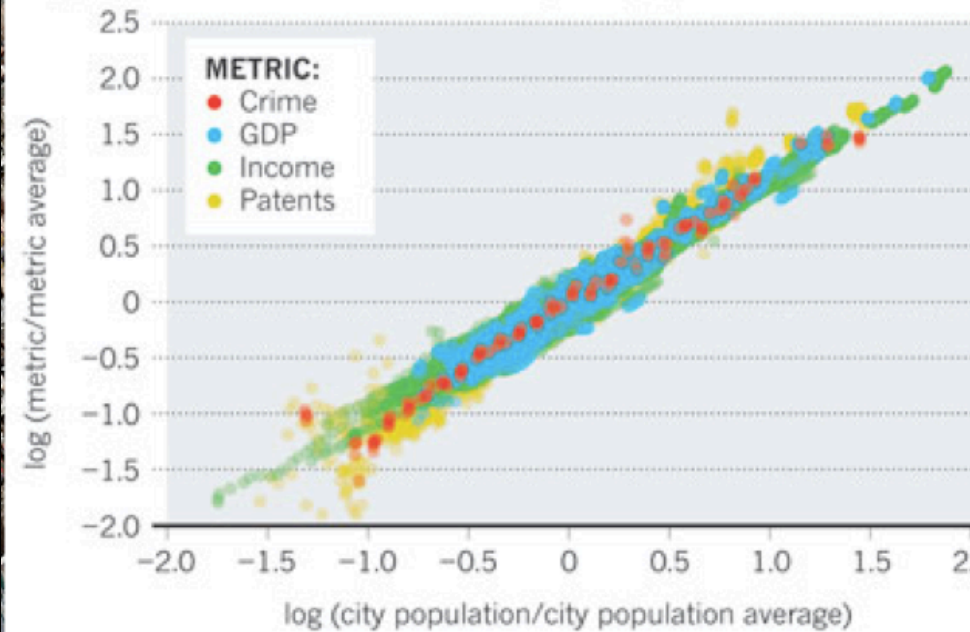


<http://www.citylab.com/design/2014/11/moving-toward-an-evolutionary-theory-of-cities/381839/>

The Pace of Life in Cities

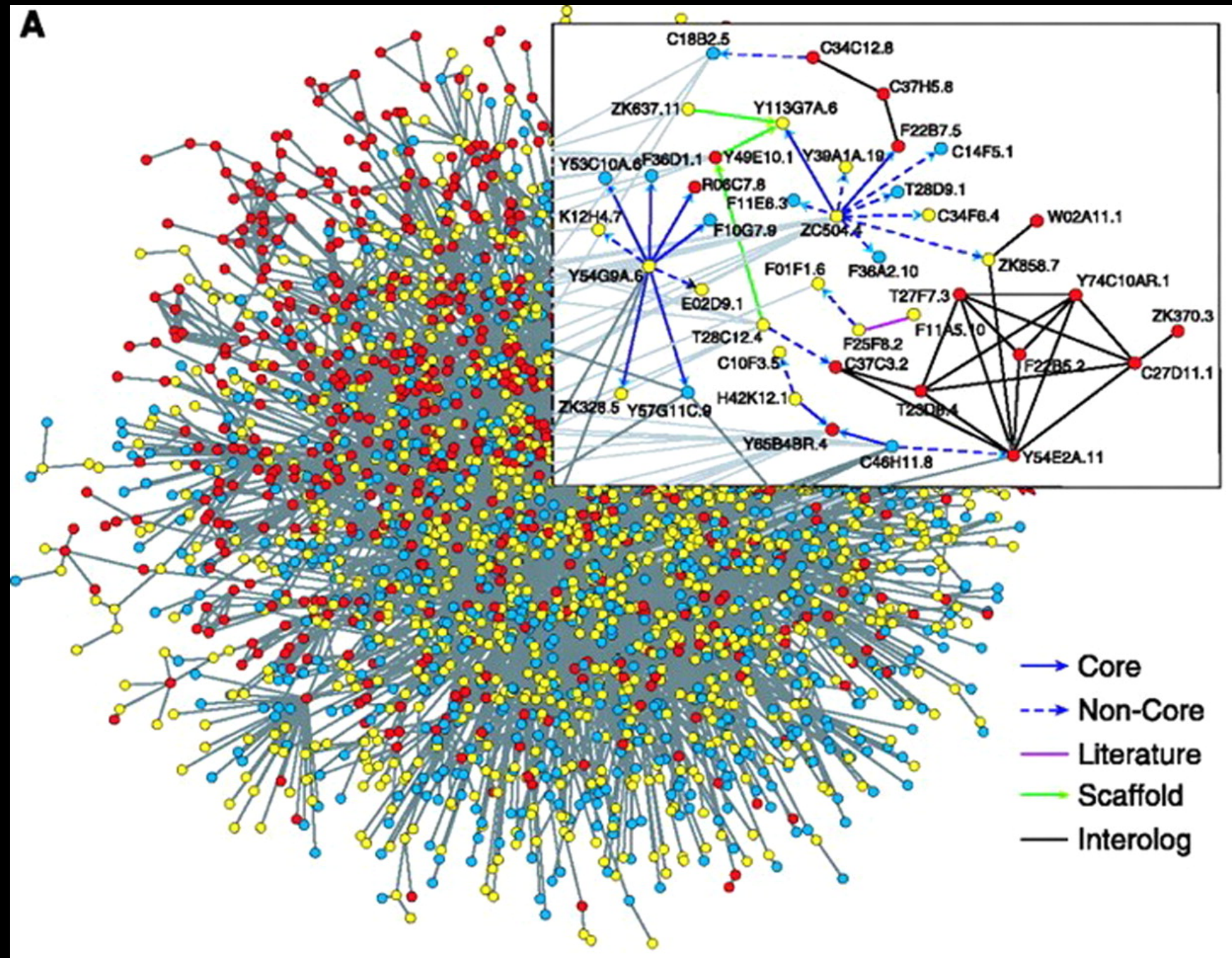
PREDICTABLE CITIES

Data from 360 US metropolitan areas show that metrics such as wages and crime scale in the same way with population size.



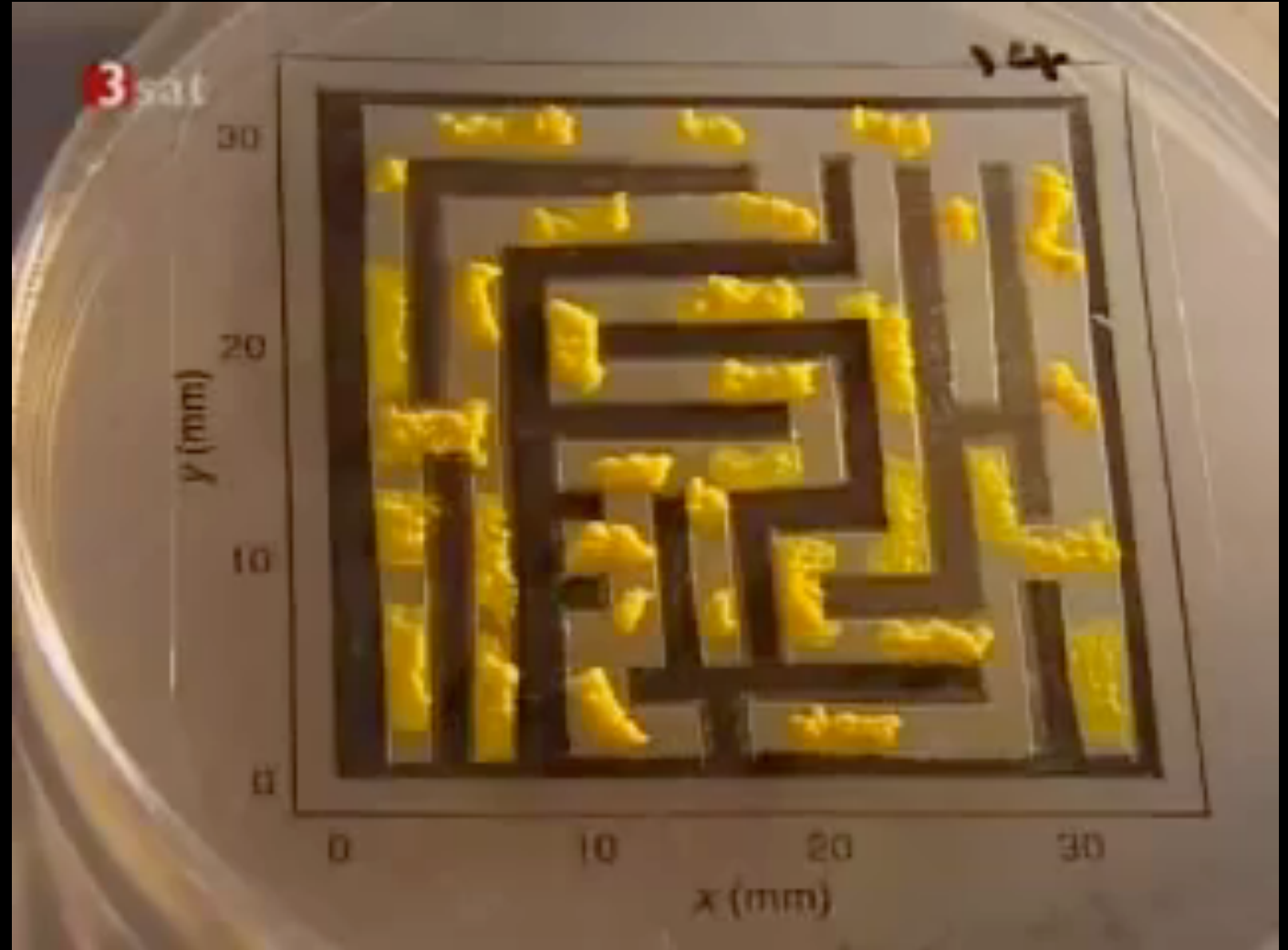
<http://www.nature.com/nature/journal/v467/n7318/full/467912a.html>

Cell protein networks



Local Interactions Leading to Global Behaviour

- Slime mold Slime Mold (Physarum Finds the Shortest Path in a Maze),.



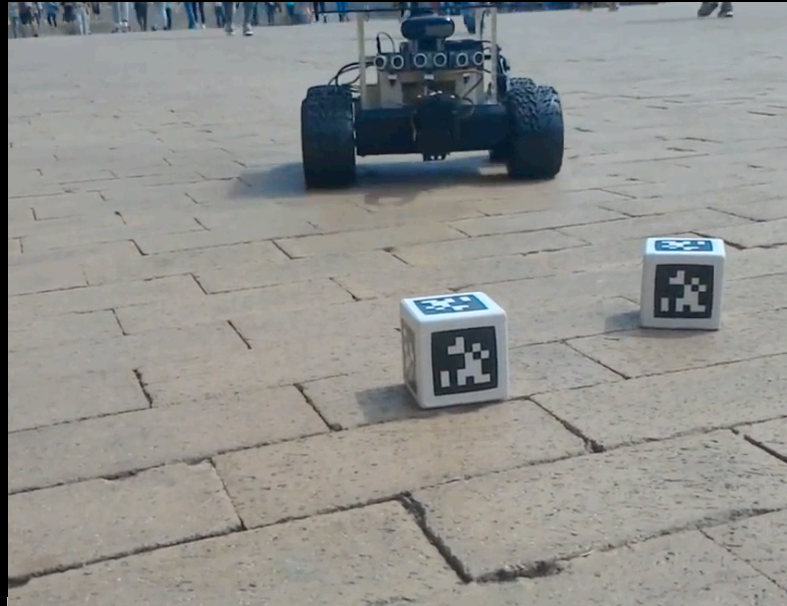
The Edge of Chaos

- Starling Murmuration



Murmurations - Ephemeral Plastic Sculptures #4

Swarm Robotics and Ant Algorithms



Sciences of Complexity



- Goals:
 - Unified theories that describe many systems
 - New computational and mathematical tools
 - Cross-disciplinary insights
- The Santa Fe Institute (founded in 1984)
 - aim is to discover .. the common fundamental principles in complex physical, computational, biological, and social systems that underlie many of the most profound problems facing science and society today.

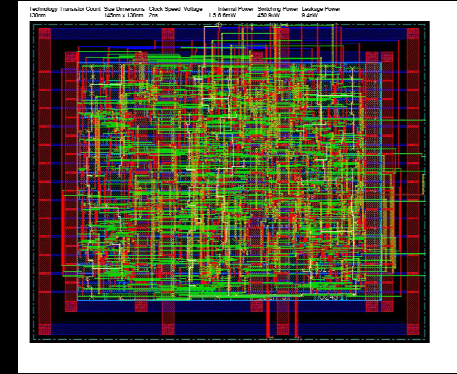
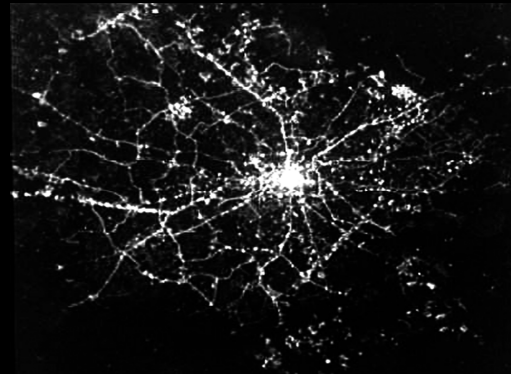
Basic Concepts of Complexity

- Dynamical Systems
 - Systems that change over time.
- Networks
 - Relationships matter
- Scaling laws: What changes as systems grow?
 - Structures often change systematically at larger/smaller scales
 - Self similarity
- Information
 - Computation writ large throughout nature
- Adaptation, competition, and evolution

Scaling Laws

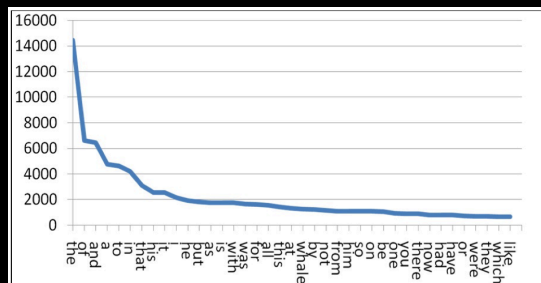
Physical and Geometric constraints determine network architecture and growth

- Network capacity limits performance as systems scale
- Metabolism, response times, power consumption
- Universal patterns in system behavior are predictable from the scaling properties of distribution networks

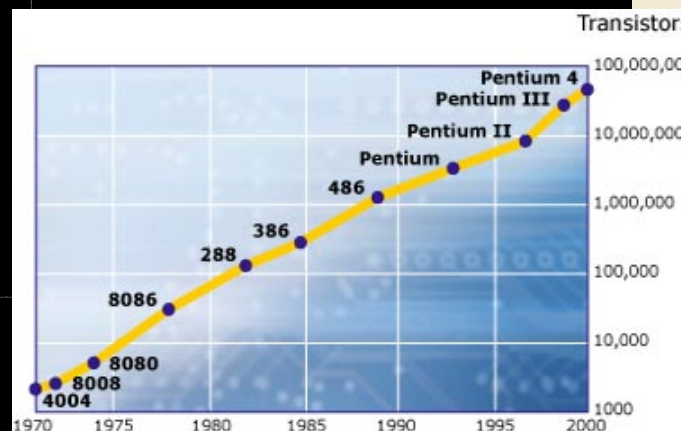
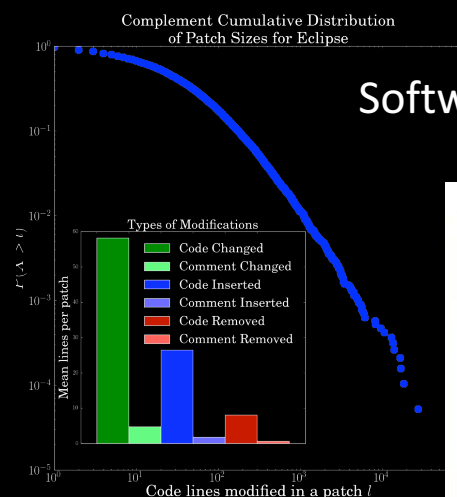
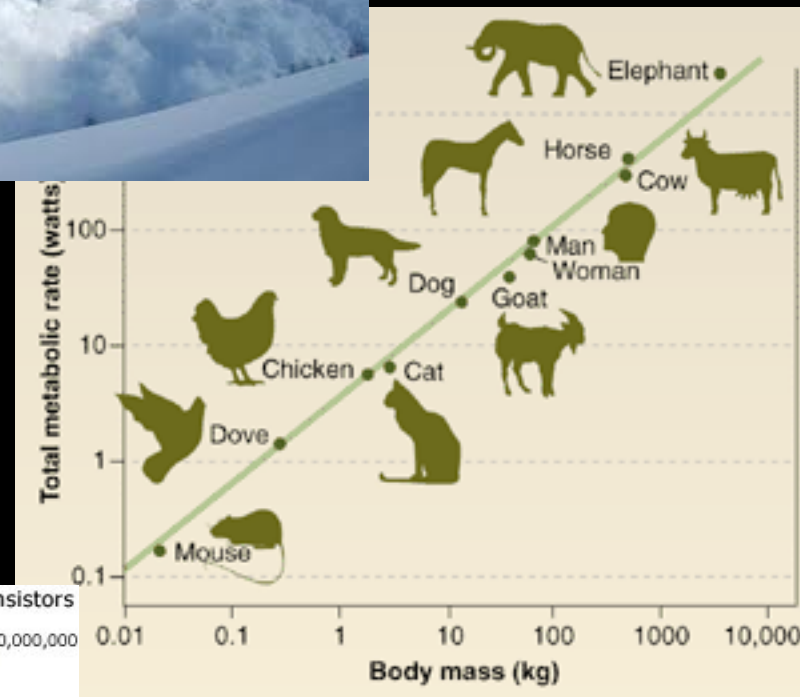


The cost of getting big

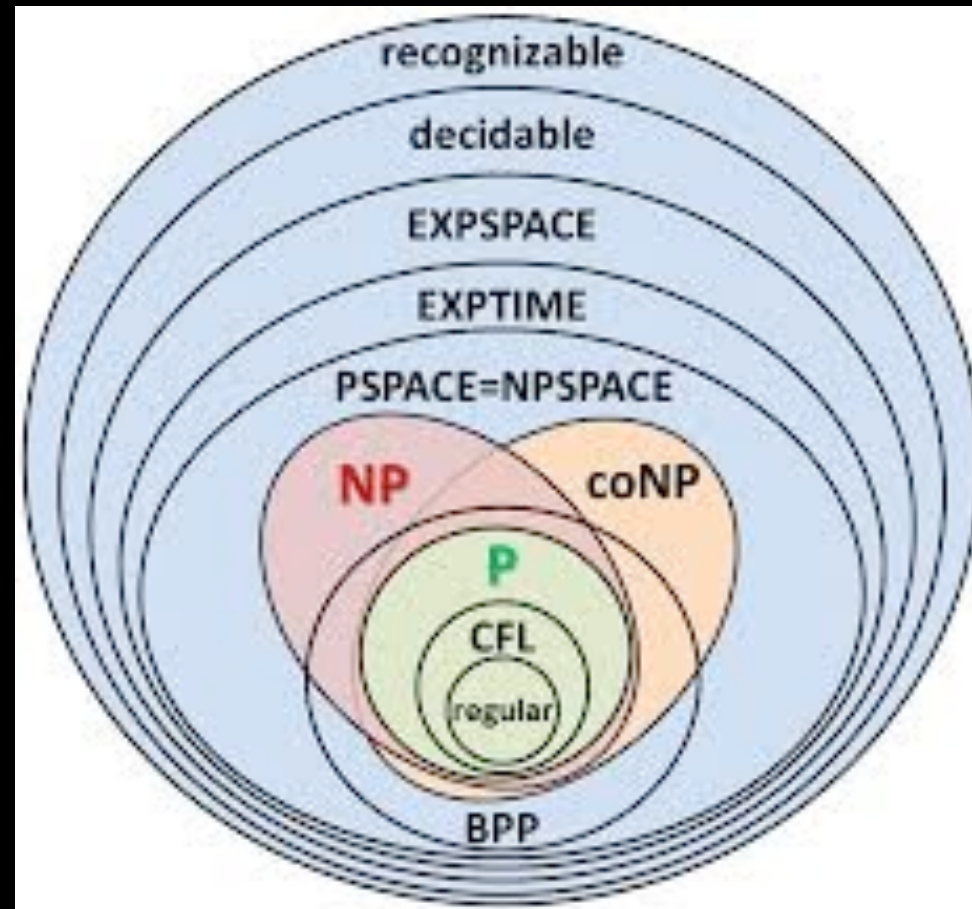
Scaling Laws



Avalanches

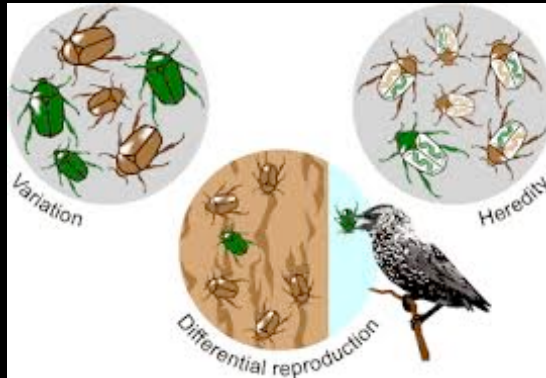


BTW: Computational complexity theory studies the scaling of algorithms



In Asymptopia!

Adaptation, Competition, Evolution

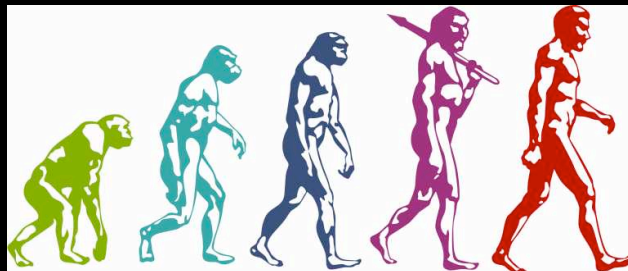


The elements

Diversity



The arms race



Iteration/Progress

Basic Concepts of Complexity

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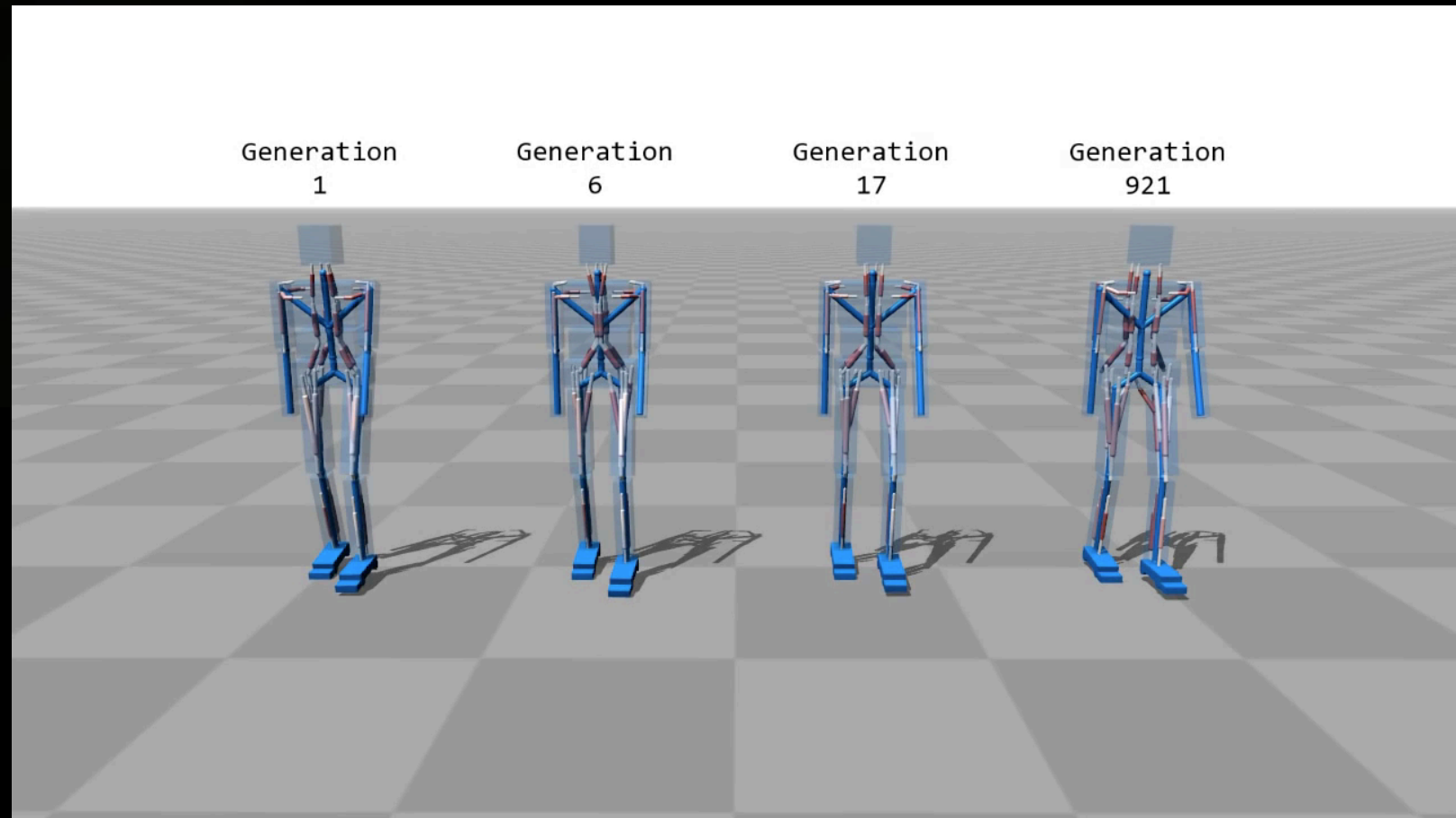
Genetic Algorithms

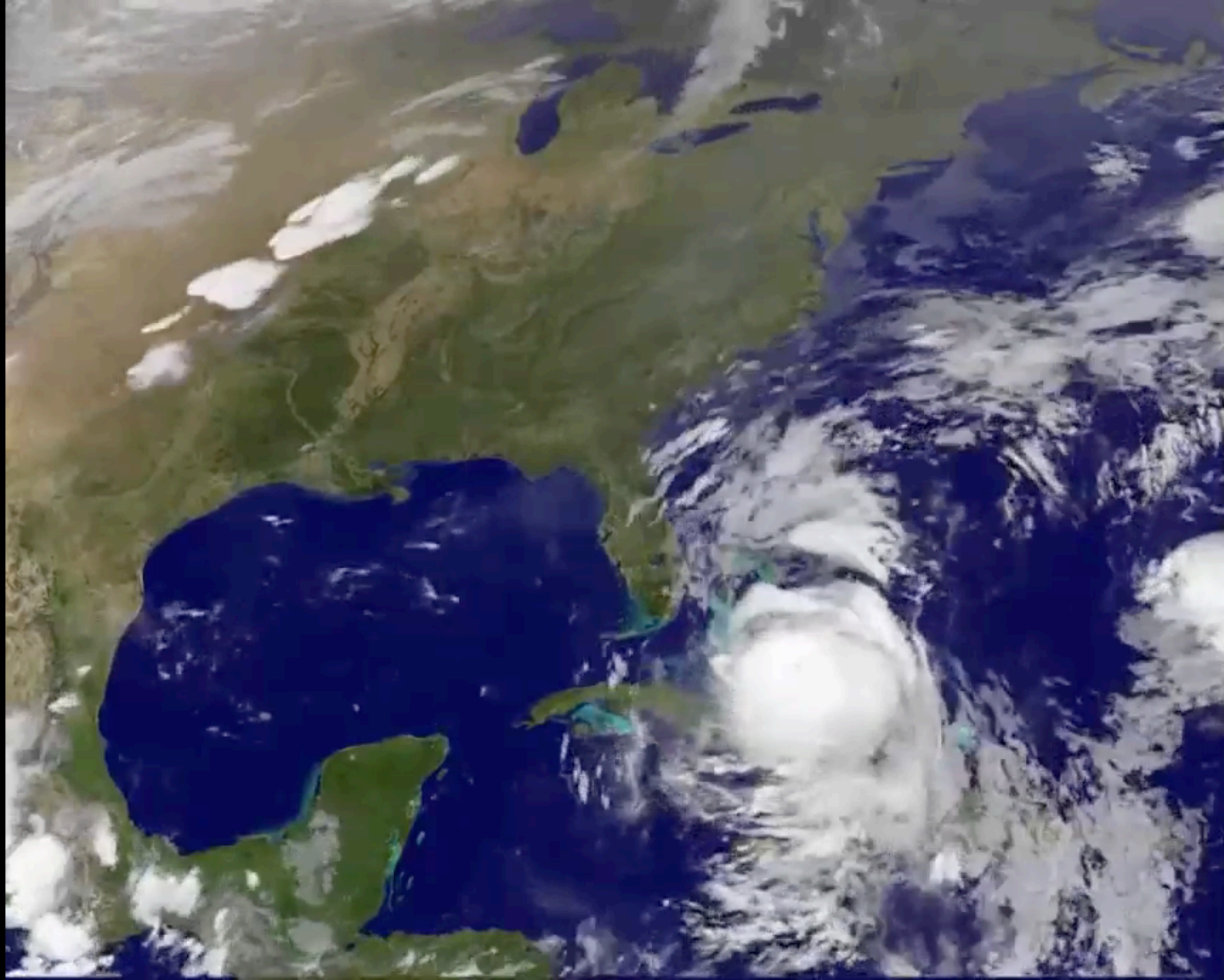
- John Holland
- We can use models of complex adaptive systems such as evolution to solve optimization problems.

- Genetic Algorithms
- Using models of evolution to optimize computer solutions

Evolved Virtual Creatures

Karl Sims





Deterministic Nonperiodic Flow¹

EDWARD N. LORENZ

Massachusetts Institute of Technology

(Manuscript received 18 November 1962, in revised form 7 January 1963)

ABSTRACT

Finite systems of deterministic ordinary nonlinear differential equations may be designed to represent forced dissipative hydrodynamic flow. Solutions of these equations can be identified with trajectories in phase space. For those systems with bounded solutions, it is found that nonperiodic solutions are ordinarily unstable with respect to small modifications, so that slightly differing initial states can evolve into considerably different states. Systems with bounded solutions are shown to possess bounded numerical solutions.

A simple system representing cellular convection is solved numerically. All of the solutions are found to be unstable, and almost all of them are nonperiodic.

The feasibility of very-long-range weather prediction is examined in the light of these results.

1. Introduction

Certain hydrodynamical systems exhibit steady-state flow patterns, while others oscillate in a regular periodic fashion. Still others vary in an irregular, seemingly haphazard manner, and, even when observed for long periods of time, do not appear to repeat their previous history.

Thus there are occasions when more than the statistics of irregular flow are of very real concern.

In this study we shall work with systems of deterministic equations which are idealizations of hydrodynamical systems. We shall be interested principally in nonperiodic solutions, i.e., solutions which never repeat their past history exactly, and where all approximate repetitions are of finite duration. Thus we shall be in-

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Current Folder: /Users/matthew/ownCloud/Teaching/CS523/LorenzCode

lorenz.m

lorenz.m~

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show2PMMovie.m calcMotilityCoefficient.m display3DFrame.m readALSADData.m lorenz.m

```
1 % Plot the Lorenz attractor. A model of a weather system.
2 function [x,y,z] = lorenz(rho, sigma, beta, initial_values, max_time, eps, rate, line_style)
3
4 options = odeset('RelTol',eps,'AbsTol',[eps eps eps/10]);
5 for t = 1:max_time
6     [T,X] = ode45(@(T,X) F(T, X, sigma, rho, beta), [0, t], initial_values, options);
7
8     x = X(:,1);
9     y = X(:,2);
10    z = X(:,3);
11
12    plot3(x, y, z, line_style)
13    pause(rate)
14    drawnow
15 end
16
17 return
18 end
19
20 function dx = F(T, X, sigma, rho, beta)
21 % Lorenz's System of Differential Equations
22
23 dx = zeros(3,1);
24 dx(1) = sigma*(X(2) - X(1));
25 dx(2) = X(1)*(rho - X(3)) - X(2);
26 dx(3) = X(1)*X(2) - beta*X(3);
27 end
```

Workspace

Name

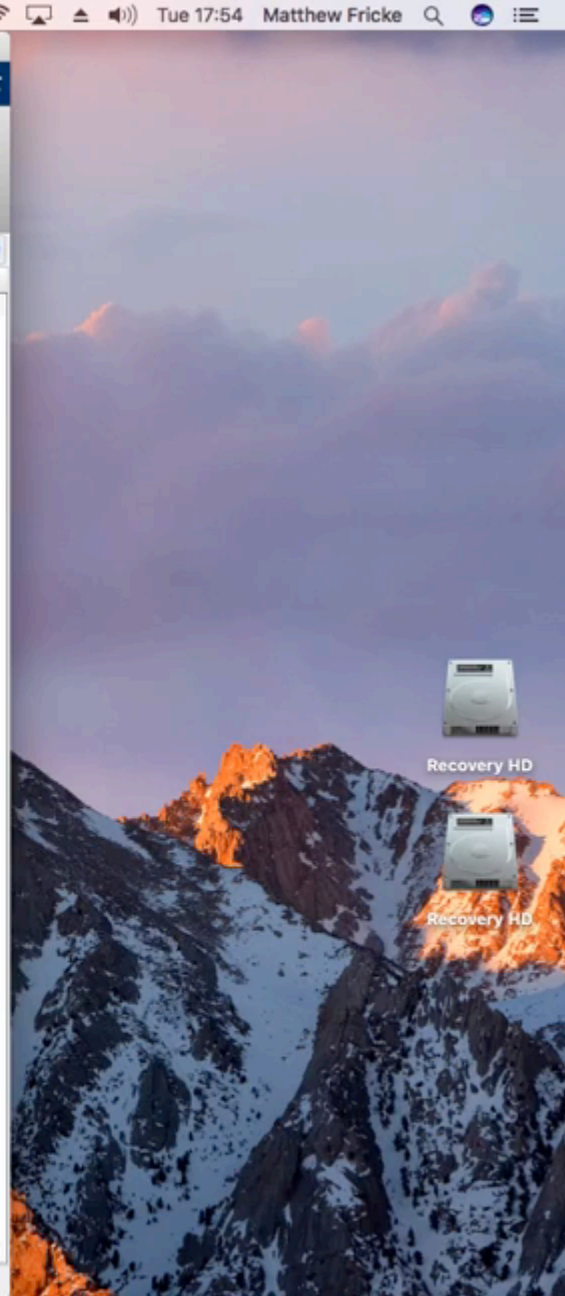
Details

Select a file to view details

Command Window

New to MATLAB? See resources for [Getting Started](#).

>>
>>
>>
>>
>>
>>
fx >> lorenz(28, 10, 8/3, [0.02, 0.01, 0.1], 100, 0.001, 0.001, 'r-');



Lorenz's Strange Attractor

- Exists in-between Order and Randomness.
- The movement through the state space is chaotic, but the attractor imposes some order on the trajectories.
- We cannot predict the trajectories but we can describe the attractor that confines the trajectories.
- This is what complex adaptive systems are about: we cannot hope to describe the microscopic behaviour of the system, but we can describe and exploit the macroscopic behaviour that results.
- the world is fundamentally unpredictable, but the attractor emerges

Models

- Complex adaptive systems were discovered by running computer models.
- Computational models are the best way to explore the behaviour of complex systems.
- In this class you will create models of systems in order to:
 - Learn about the system.
 - Exploit the system to solve problems.

For Monday your homework is:

- read a and b under Section I: Background
- If you are a graduate student think about a paper listed on the course website to present during the semester.

Some are advanced, be sure you have the background required. Many require no background.

- Sign up for the mailing list.
- See me in office hours if you are not registered.