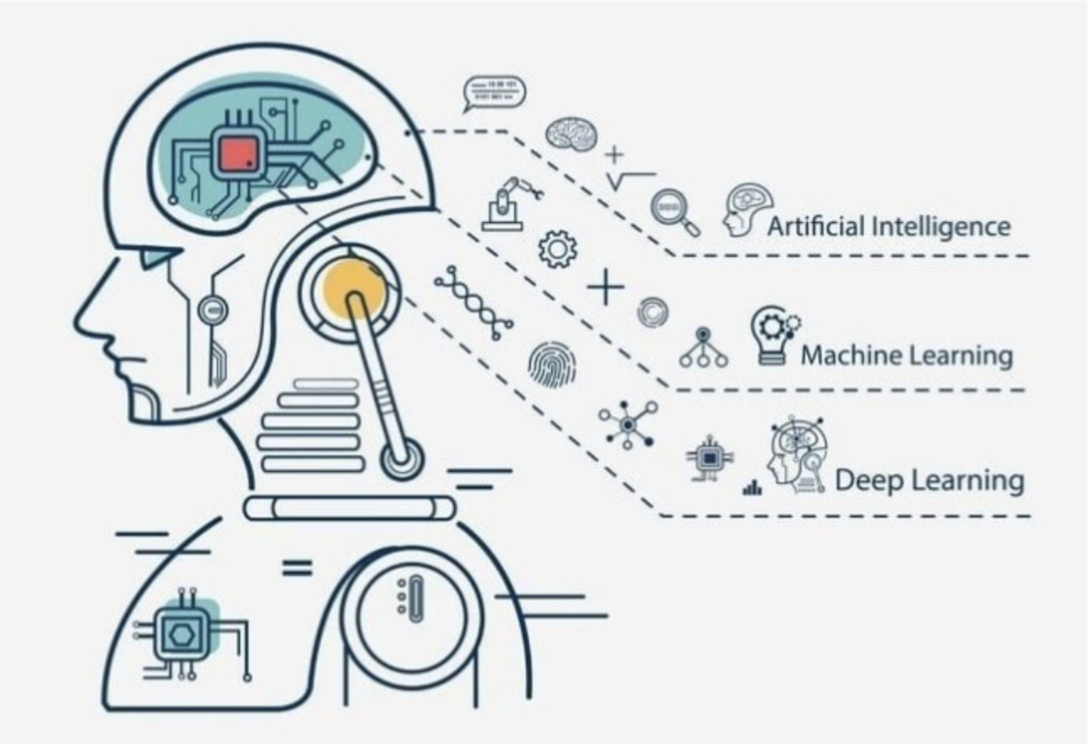


AI and Complex Systems

张江

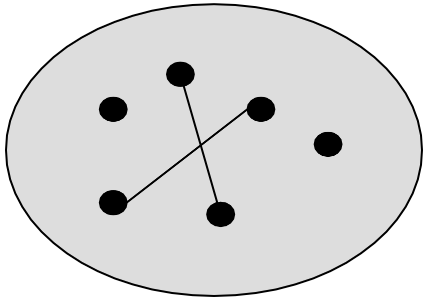
北京师范大学系统科学学院教授

集智俱乐部、集智学园创始人

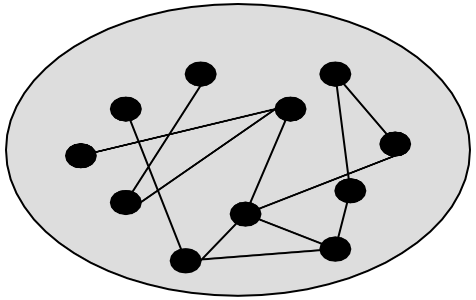
集智研究中心理事长

What are Complex Systems?

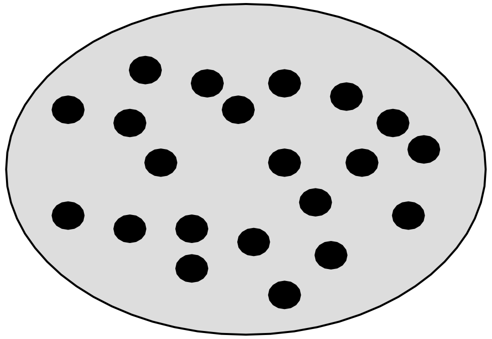
What are Complex Systems?



简单系统

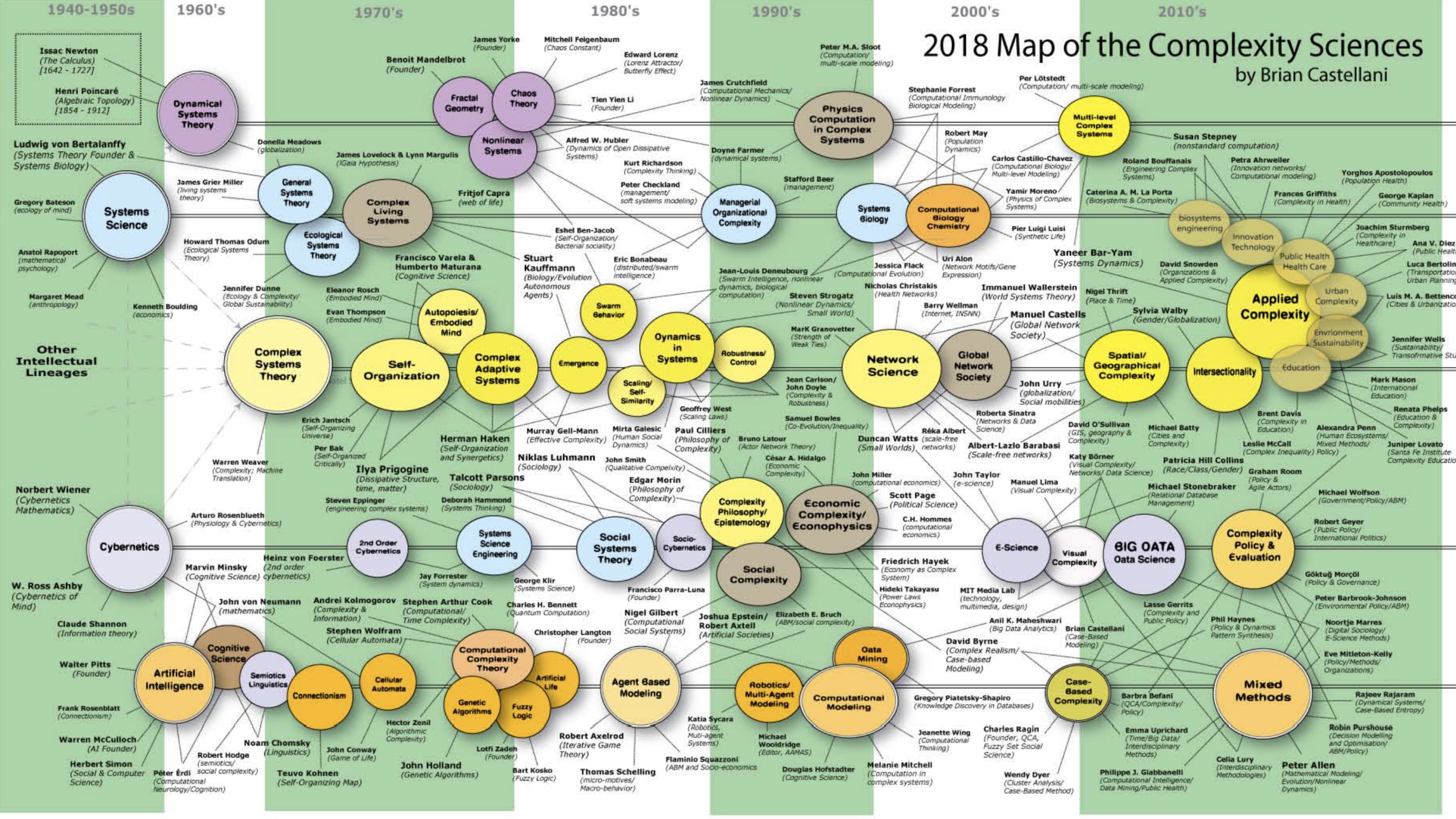


复杂系统



无组织的随机系统

What is complexity science?



2018 Map of the Complexity Sciences
by Brian Castellani
1940-1950s
1960's
1970's
1980's
1990's
2000's
2010's
Issac Newton (The Calculus) [1642 - 1727]
Henri Poincaré (Algebraic Topology) [1854 - 1912]
Dynamical Systems Theory
Ludwig von Bertalanffy (Systems Theory Founder & Systems Biology)
Gregory Bateson (ecology of mind)
Systems Science
Anatol Rapoport (mathematical psychology)
Margaret Mead (anthropology)
Kenneth Boulding (economics)
Other Intellectual Lineages
Norbert Wiener (Cybernetics Mathematics)
Cybernetics
W. Ross Ashby (Cybernetics of Mind)
Claude Shannon (Information theory)
Walter Pitts (Founder)
Artificial Intelligence
Frank Rosenblatt (Connectionism)
Warren McCulloch (AI Founder)
Herbert Simon (Social & Computer Science)
Péter Érdi (Computational Neurology/Cognition)
Robert Hodge (semiotics/ social complexity)
Noam Chomsky (Linguistics)
Teuvo Kohnen (Self-Organizing Map)
Cognitive Science
Semiotics Linguistics
Connectionism
Marvin Minsky (Cognitive Science)
John von Neumann (mathematics)
Heinz von Foerster (2nd order cybernetics)
Arturo Rosenblueth (Physiology & Cybernetics)
Warren Weaver (Complexity; Machine Translation)
Complex Systems Theory
Donella Meadows (globalization)
James Grier Miller (living systems theory)
General Systems Theory
Howard Thomas Odum (Ecological Systems Theory)
Ecological Systems Theory
Jennifer Dunne (Ecology & Complexity/ Global Sustainability)
James Lovelock & Lynn Margulis (IGaia Hypothesis)
Complex Living Systems
Fritjof Capra (web of life)
Francisco Varela & Humberto Maturana (Cognitive Science)
Eleanor Rosch (Embodied Mind)
Evan Thompson (Embodied Mind)
Autopoiesis/ Embodied Mind
Self-Organization
Complex Adaptive Systems
Erich Jantsch (Self-Organizing Universe)
Per Bak (Self-Organized Criticality)
Ilya Prigogine (Dissipative Structure, time, matter)
Herman Haken (Self-Organization and Synergetics)
Talcott Parsons (Sociology)
Steven Eppinger (engineering complex systems)
Deborah Hammond (Systems Thinking)
2nd Order Cybernetics
Systems Science Engineering
Jay Forrester (System dynamics)
George Klir (Systems Science)
Andrei Kolmogorov (Complexity & Information)
Stephen Arthur Cook (Computational/ Time Complexity)
Charles H. Bennett (Quantum Computation)
Stephen Wolfram (Cellular Automata)
Christopher Langton (Founder)
Cellular Automata
Computational Complexity Theory
Artificial Life
Genetic Algorithms
Fuzzy Logic
Hector Zenil (Algorithmic Complexity)
John Conway (Game of Life)
John Holland (Genetic Algorithms)
Lotfi Zadeh (Founder)
Bart Kosko (Fuzzy Logic)
James Yorke (Founder)
Mitchell Feigenbaum (Chaos Constant)
Benoit Mandelbrot (Founder)
Edward Lorenz (Lorenz Attractor/ Butterfly Effect)
Fractal Geometry
Chaos Theory
Tien Yien Li (Founder)
Nonlinear Systems
Alfred W. Hubler (Dynamics of Open Dissipative Systems)
Eshel Ben-Jacob (Self-Organization/ Bacterial sociality)
Stuart Kauffmann (Biology/Evolution Autonomous Agents)
Eric Bonabeau (distributed/swarm intelligence)
Swarm Behavior
Emergence
Dynamics in Systems
Robustness/ Control
Scaling/ Self-Similarity
Murray Gell-Mann (Effective Complexity)
Niklas Luhmann (Sociology)
Mirta Galesic (Human Social Dynamics)
Geoffrey West (Scaling Laws)
Paul Cilliers (Philosophy of Complexity)
John Smith (Qualitative Compelxity)
Edgar Morin (Philosophy of Complexity)
Social Systems Theory
Socio-Cybernetics
Francisco Parra-Luna (Founder)
Nigel Gilbert (Computational Social Systems)
Agent Based Modeling
Robert Axelrod (Iterative Game Theory)
Thomas Schelling (micro-motives/ Macro-behavior)
Flaminio Squazzoni (ABM and Socio-economics)
Katia Sycara (Robotics, Muti-agent Systems)
James Crutchfield (Computational Mechanics/ Nonlinear Dynamics)
Physics Computation in Complex Systems
Peter M.A. Sloot (Computation/ multi-scale modeling)
Doyne Farmer (dynamical systems)
Kurt Richardson (Complexity Thinking)
Peter Checkland (management/ soft systems modeling)
Stafford Beer (management)
Managerial Organizational Complexity
Jean-Louis Deneubourg (Swarm Intelligence, nonlinear dynamics, biological computation)
Steven Strogatz (Nonlinear Dynamics/ Small World)
Mark Granovetter (Strength of Weak Ties)
Jean Carlson/ John Doyle (Complexity & Robustness)
Samuel Bowles (Co-Evolution/Inequality)
Bruno Latour (Actor Network Theory)
César A. Hidalgo (Economic Complexity)
Complexity Philosophy/ Epistemology
Economic Complexity/ Econophysics
Social Complexity
Joshua Epstein/ Robert Axtell (Artificial Societies)
Elizabeth E. Bruch (ABM/social complexity)
Robotics/ Multi-Agent Modeling
Computational Modeling
Data Mining
Michael Wooldridge (Editor, AAMAS)
Douglas Hofstadter (Cognitive Science)
Melanie Mitchell (Computation in complex systems)
Stephanie Forrest (Computational Immunology Biological Modeling)
Robert May (Population Dynamics)
Carlos Castillo-Chavez (Computational Biology/ Multi-level Modeling)
Yamir Moreno (Physics of Complex Systems)
Systems Biology
Computational Biology Chemistry
Pier Luigi Luisi (Synthetic Life)
Jessica Flack (Computational Evolution)
Uri Alon (Network Motifs/Gene Expression)
Nicholas Christakis (Health Networks)
Barry Wellman (Internet, INSNN)
Immanuel Wallerstein (World Systems Theory)
Manuel Castells (Global Network Society)
Network Science
Global Network Society
John Urry (globalization/ Social mobilities)
Roberta Sinatra (Networks & Data Science)
Réka Albert (scale-free networks)
Duncan Watts (Small Worlds)
Albert-Lazlo Barabasi (Scale-free networks)
John Miller (computational economics)
Scott Page (Political Science)
C.H. Hommes (computational economics)
John Taylor (e-science)
Manuel Lima (Visual Complexity)
Friedrich Hayek (Economy as Complex System)
Hideki Takayasu (Power Laws Econophysics)
MIT Media Lab (technology, multimedia, design)
E-Science
Visual Complexity
BIG DATA Data Science
Anil K. Maheshwari (Big Data Analytics)
David Byrne (Complex Realism/ Case-based Modeling)
Gregory Piatetsky-Shapiro (Knowledge Discovery in Databases)
Jeanette Wing (Computational Thinking)
Charles Ragin (Founder, QCA, Fuzzy Set Social Science)
Wendy Dyer (Cluster Analysis/ Case-Based Method)
Case-Based Complexity
Brian Castellani (Case-Based Modeling)
Per Lötstedt (Computation/ multi-scale modeling)
Multi-level Complex Systems
Susan Stepney (nonstandard computation)
Roland Bouffanais (Engineering Complex Systems)
Petra Ahrweiler (Innovation networks/ Computational modeling)
Yorghos Apostolopoulos (Population Health)
Caterina A. M. La Porta (Biosystems & Complexity)
Frances Griffiths (Complexity in Health)
George Kaplan (Community Health)
biosystems engineering
Innovation Technology
Public Health Health Care
Joachim Sturmberg (Complexity in Healthcare)
Ana V. Diez (Public Healt
Luca Bertolin (Transportatio Urban Plannin
Yaneer Bar-Yam (Systems Dynamics)
David Snowden (Organizations & Applied Complexity)
Applied Complexity
Urban Complexity
Luis M. A. Bettenc (Cities & Urbanizatio
Nigel Thrift (Place & Time)
Sylvia Walby (Gender/Globalization)
Envrionment Sustainability
Jennifer Wells (Sustainability/ Transofrmative Stu
Spatial/ Geographical Complexity
Intersectionality
Education
Mark Mason (International Education)
Renata Phelps (Education & Complexity)
David O'Sullivan (GIS, geography & Complexity)
Michael Batty (Cities and Complexity)
Brent Davis (Complexity in Education)
Alexandra Penn (Human Ecosystems/ Mixed Methods/ Policy)
Juniper Lovato (Santa Fe Institute Complexity Educatio
Leslie McCall (Complex Inequality)
Katy Börner (Visual Complexity/ Networks/ Data Science)
Patricia Hill Collins (Race/Class/Gender)
Graham Room (Policy & Agile Actors)
Michael Stonebraker (Relational Database Management)
Michael Wolfson (Government/Policy/ABM)
Complexity Policy & Evaluation
Robert Geyer (Public Policy/ International Politics)
Göktuğ Morçöl (Policy & Governance)
Peter Barbrook-Johnson (Environmental Policy/ABM)
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Phil Haynes (Policy & Dynamics Pattern Synthesis)
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Mixed Methods
Barbra Befani (QCA/Complexity/ Policy)
Rajeev Rajaram (Dynamical Systems/ Case-Based Entropy)
Emma Uprichard (Time/Big Data/ Interdisciplinary Methods)
Robin Purshouse (Decision Modelling and Optimisation/ ABM/Policy)
Philippe J. Giabbanelli (Computational Intelligence/ Data Mining/Public Health)
Celia Lury (Interdisciplinary Methodologies)
Peter Allen (Mathematical Modeling/ Evolution/Nonlinear Dynamics)

（复杂）系统科学的演进

老三论
1930-1960

- 系统论
- 信息论
- 控制论

新三论
1970-1990

- 耗散结构论
- 协同学
- 突变论
- 分形
- 混沌

圣塔菲学派
1990-2000

- 多主体建模
- 人工生命
- 元胞自动机
- 布尔网络
- ……

复杂网络
2000-2010

- ER随机网：图论+统计
- 复杂网络：小世界、无标度（图论+统计物理）
- 网络科学

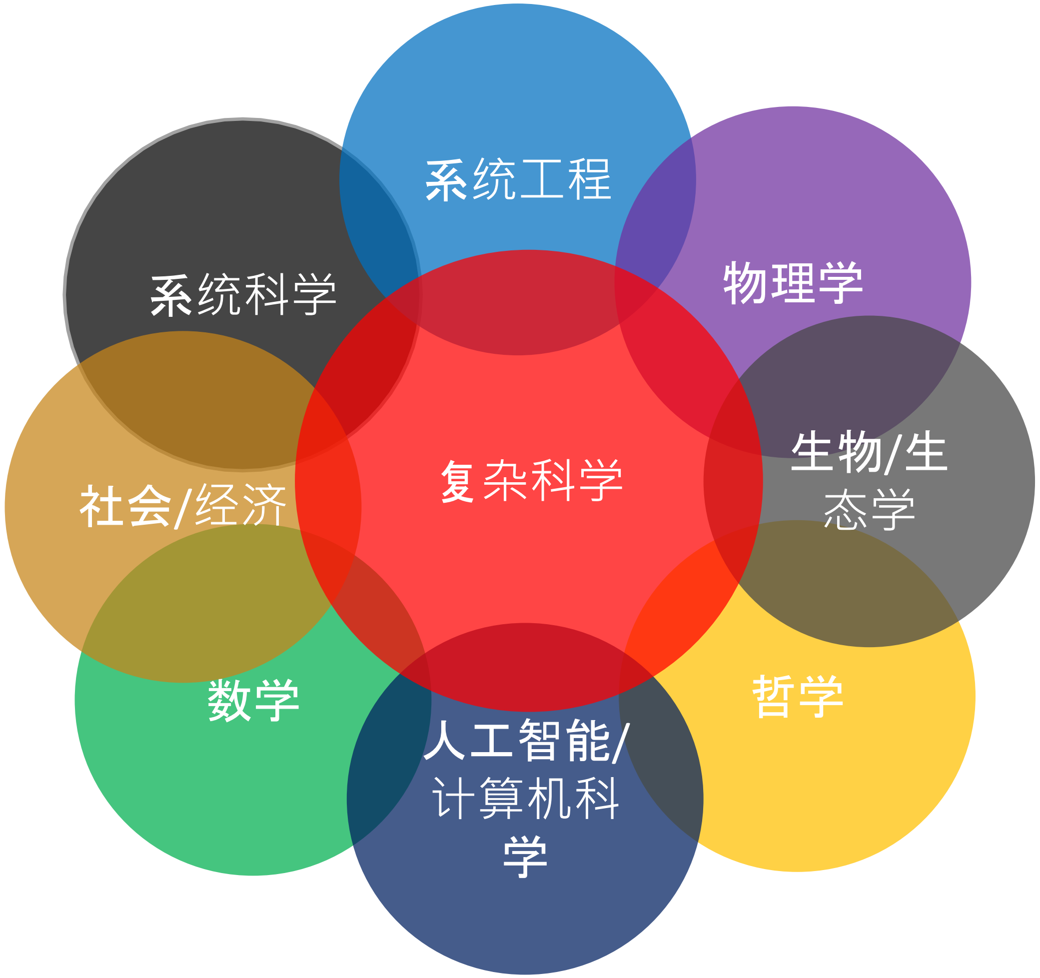
数据驱动
2010-2020

- 复杂系统物理学
- Scaling
- 计算社会科学
- ……

AI？因果？
?

What is complexity science?

What is complexity science?



Outline

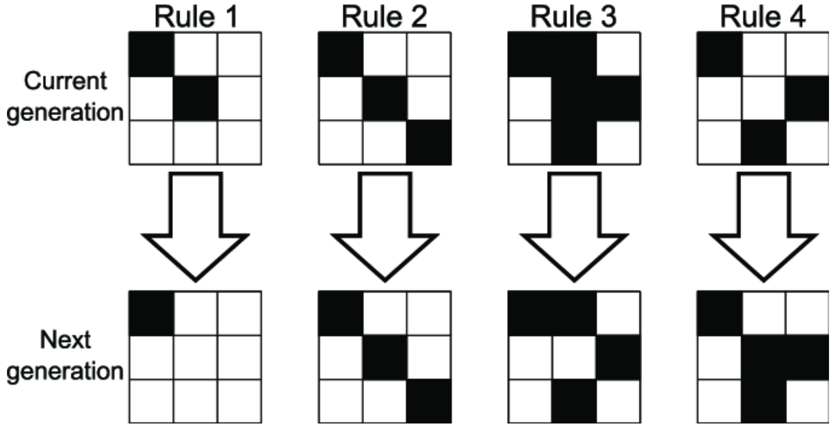
- AI for complex systems
- Complexity science for AI

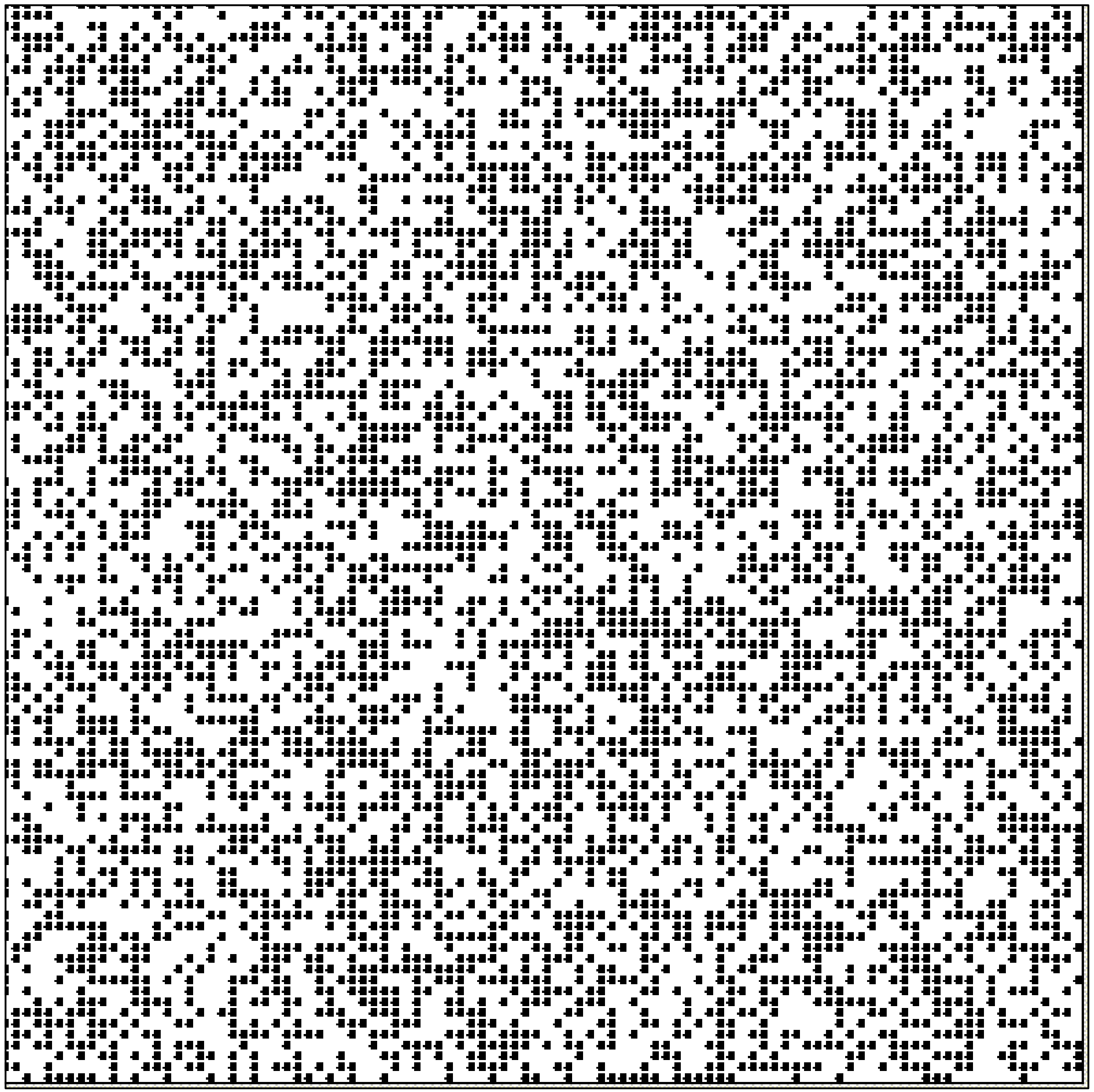
Outline

- AI for complex systems
  - Complex Systems and Modelling Methods
  - Representation & Generation
  - Dynamics Learning
  - Network Reconstruction
  - Multi-scale Modelling
  - Simulation, optimization, and control
- Complexity science for AI

Game of Life

- Conway's GAME of LIFE
- Each cell has 8 neighbors
- Change color according to neighbors
- Studying complexity

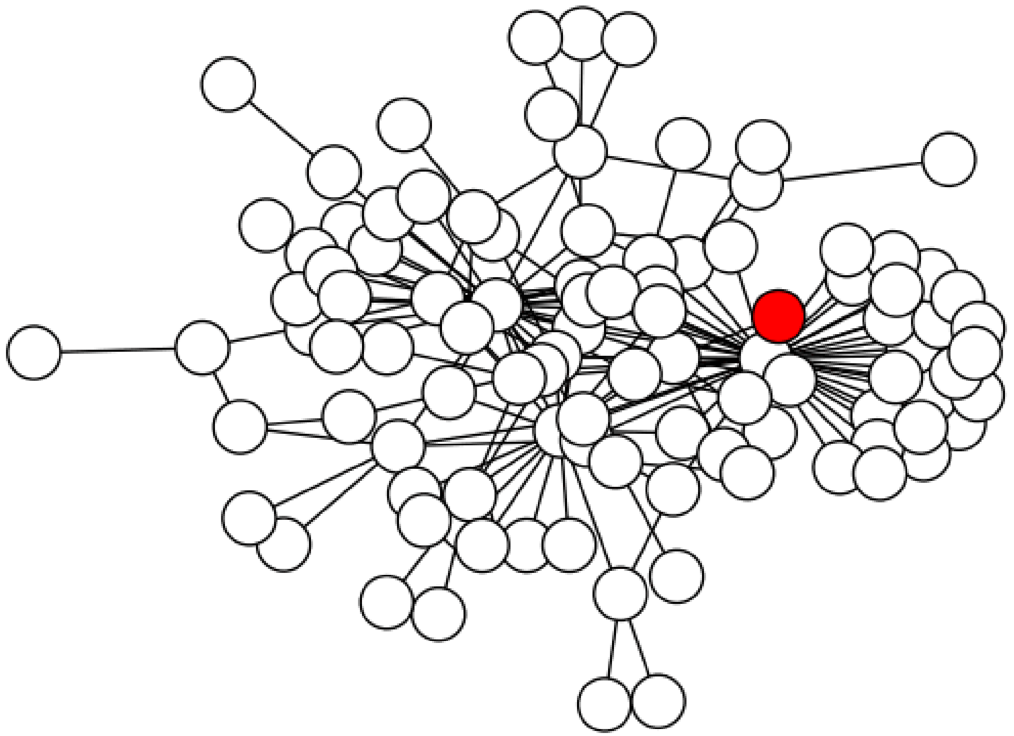




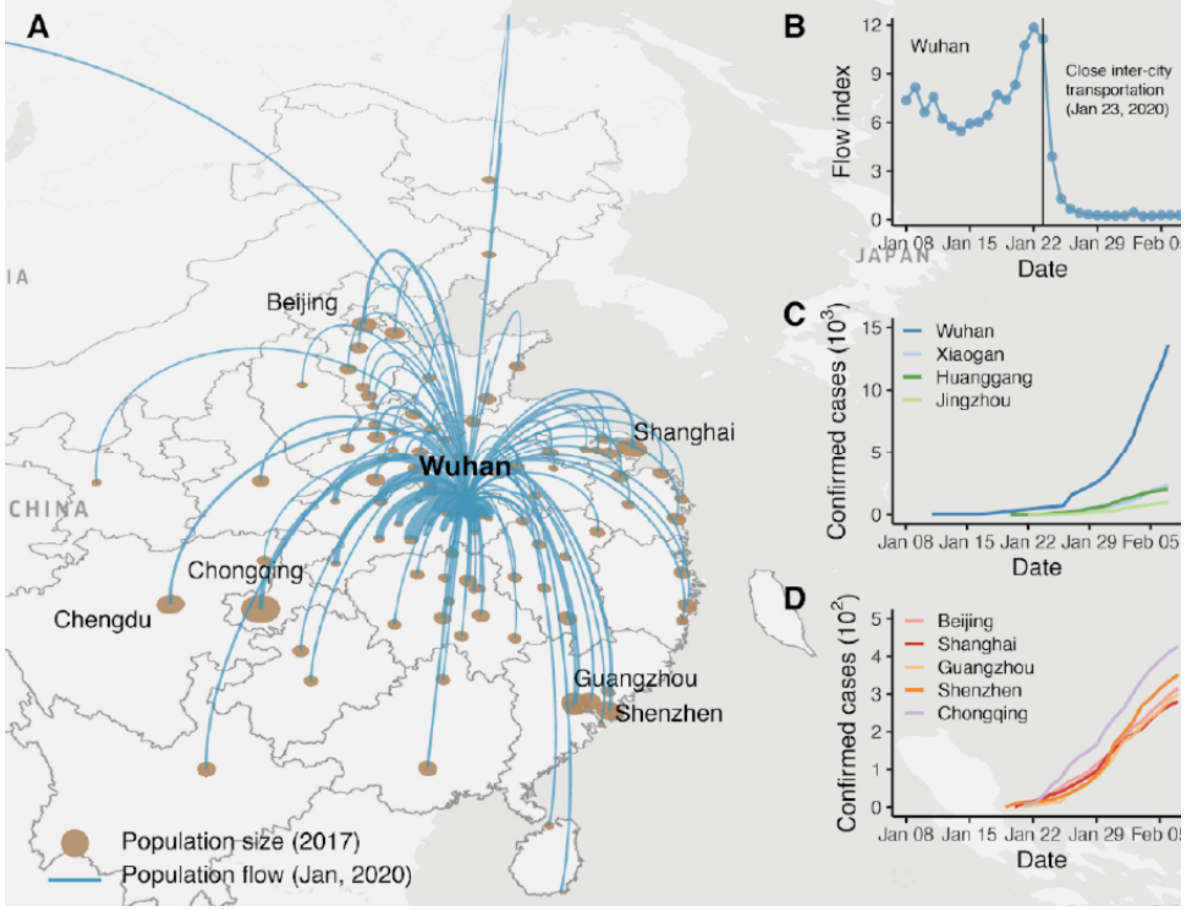
SIR on Network

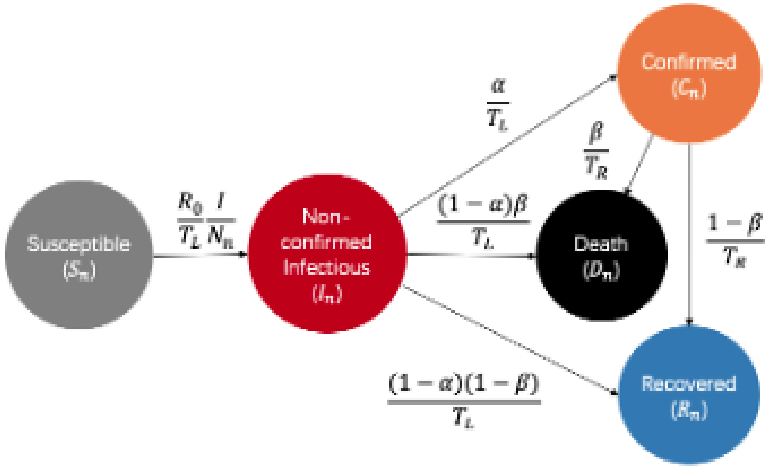
- SIR model
- S node (white) can be infected by the infectious node (red)
- Infectious node can turn to recovered (grey)

First infection = neighbour of highest degree node
time = 0



Epidemic





$$\partial s_n / \partial t = -\frac{R_0}{T_L} s_n i_n + \omega \sum_{m \neq n} P_{mn}(s_m - s_n)$$

$$\partial i_n / \partial t = \frac{R_0}{T_L} s_n i_n - \frac{\alpha}{T_L} i_n - \frac{1-\alpha}{T_L} i_n + \omega \sum_{m \neq n} P_{mn}(i_m - i_n)$$

$$\partial c_n / \partial t = \frac{\alpha}{T_L} i_n - \frac{1}{T_R} c_n$$

$$\partial d_n / \partial t = \frac{\beta(1-\alpha)}{T_L} i_n + \frac{\beta}{T_R} c_n$$

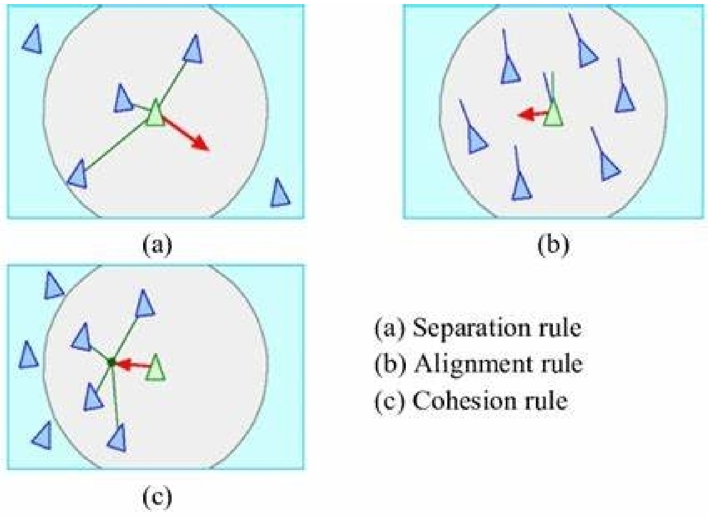
$$r_n = 1 - s_n - j_n - c_n - d_n$$

Jiang Zhang,et al. Investigating time, strength, and duration of measures in controlling the spread of COVID-19 using a networked meta-population model; Nonlinear Dynamics 101(10223) (2020)

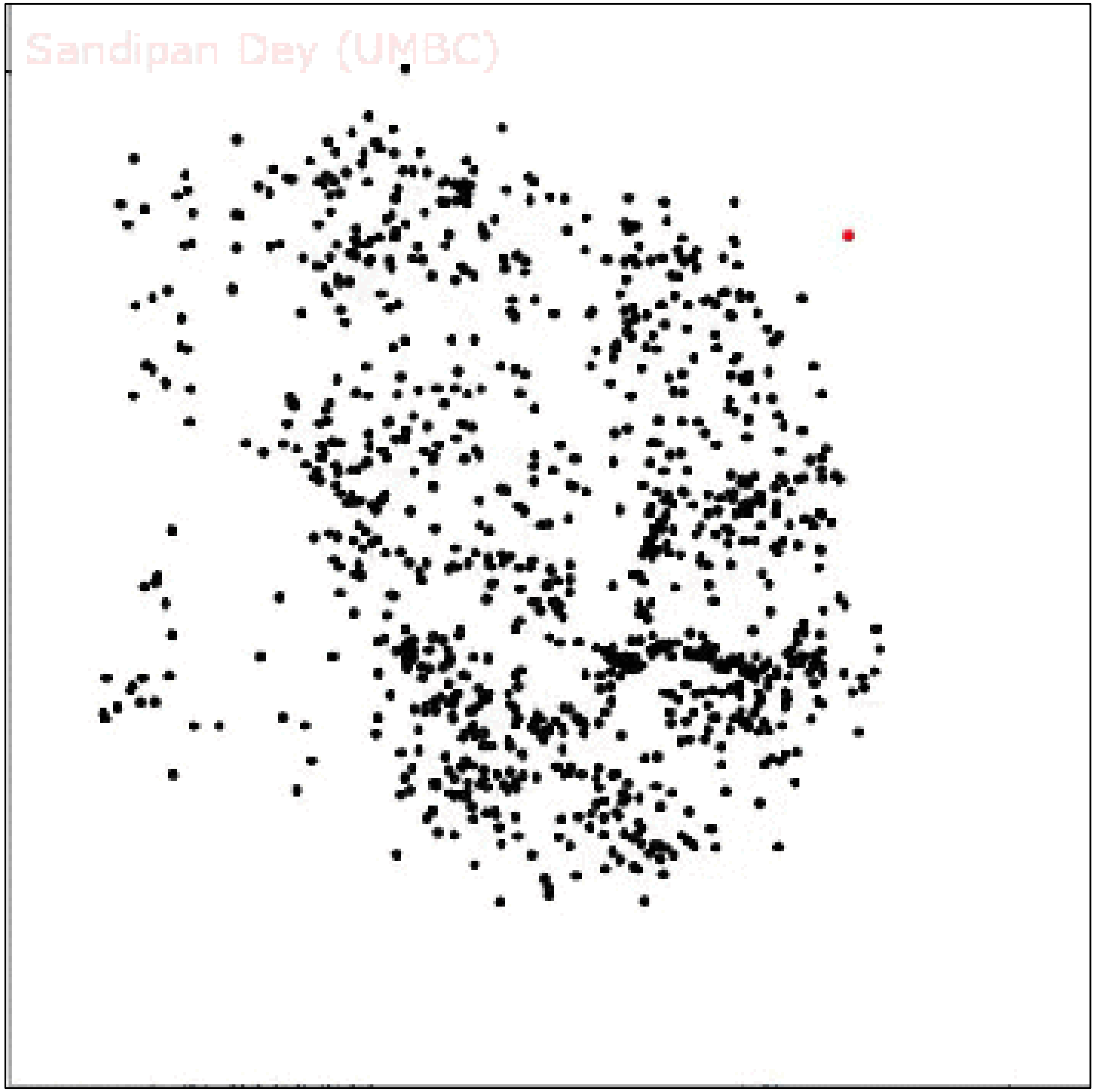
集智斑图 Swarma Pattern

Boid Model

- Boid model
- Each boid follows 3 rules
  - Cohesion
  - Alignment
  - Separation



(a) Separation rule
(b) Alignment rule
(c) Cohesion rule



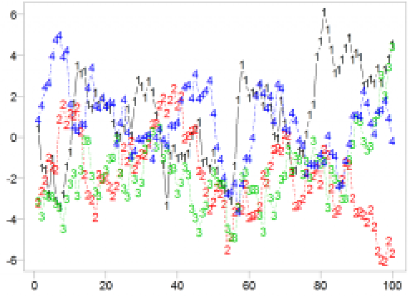
Summary

- Benefits:
  - Simple & concise
  - More insightful
  - More theoretical analysis
  - Cheap computation
- Drawbacks:
  - Too Simple to explain complex phenomenon
  - Difficult to incorporate real data
  - Poor prediction accuracy
  - Rely on Human Heuristics
  - Case by Case

Automated Modelling of Complex Systems

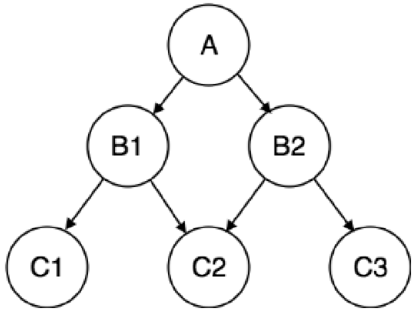
Complex System

Behavior (observations)



AI systems

Models



Prediction, Simulation,
Optimization, Controls

Outline

- AI for complex systems
  - Complex Systems and Modelling Methods
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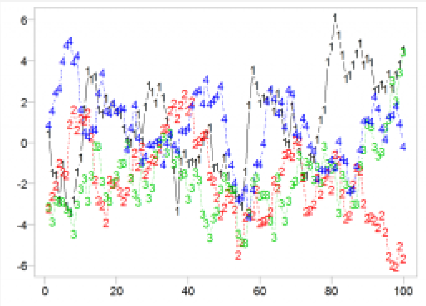
  - Dynamics Learning
  - Network Reconstruction
  - Multi-scale Modelling
  - Simulation, optimization, and control
- Complexity science for AI

Representation & Generation

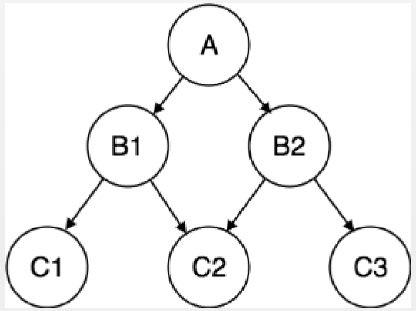
Behavior (observations)



Representation

AI systems

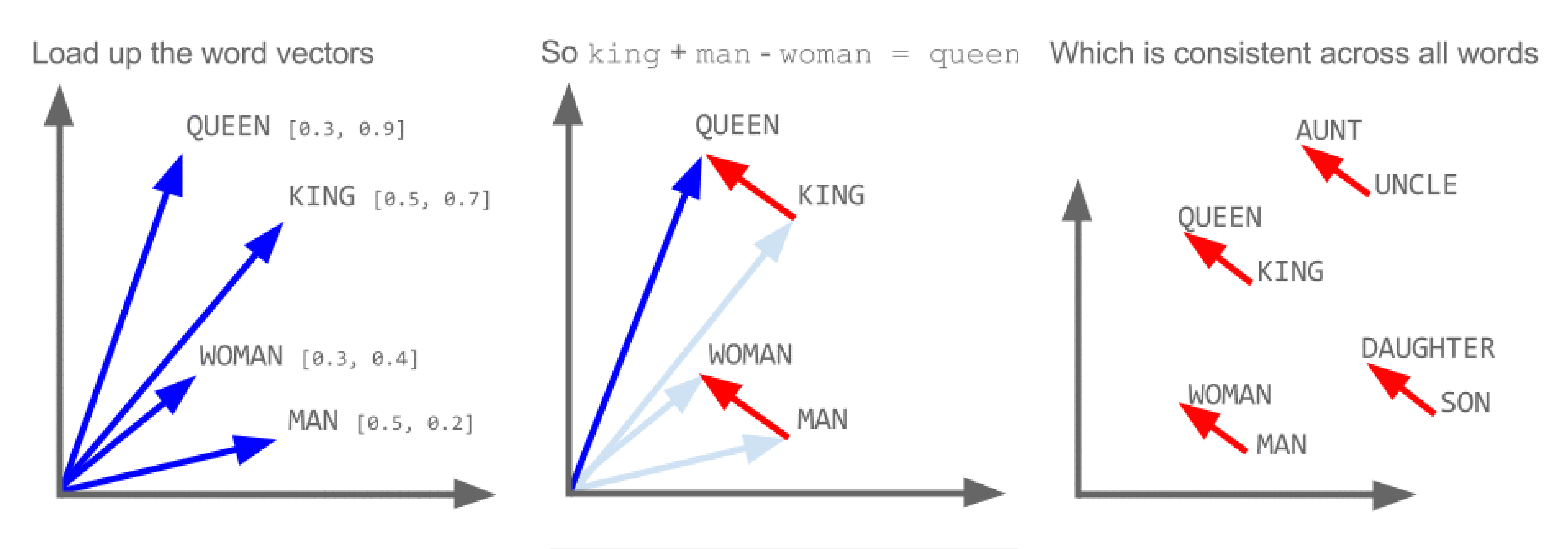
Models



Predict Next Time Step

Generation

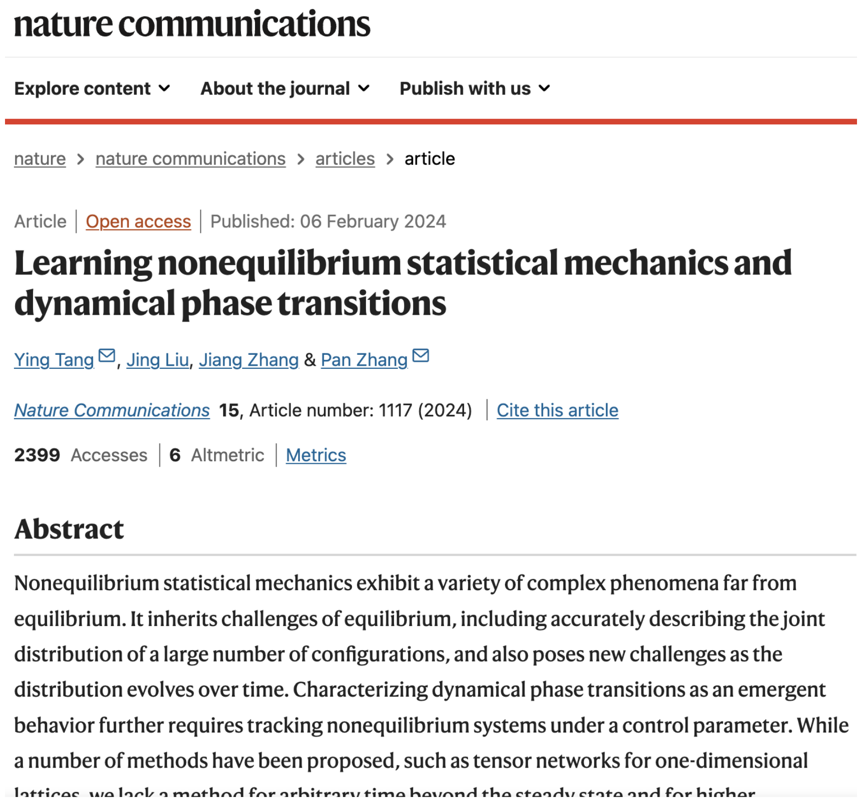
Word2Vec



Load up the word vectors
QUEEN [0.3, 0.9]
KING [0.5, 0.7]
WOMAN [0.3, 0.4]
MAN [0.5, 0.2]
So king + man - woman = queen
QUEEN
KING
WOMAN
MAN
Which is consistent across all words
AUNT
UNCLE
QUEEN
KING
DAUGHTER
SON
WOMAN
MAN

Generative AI

Learning nonequilibrium statistical mechanics and dynamical phase transitions



nature communications

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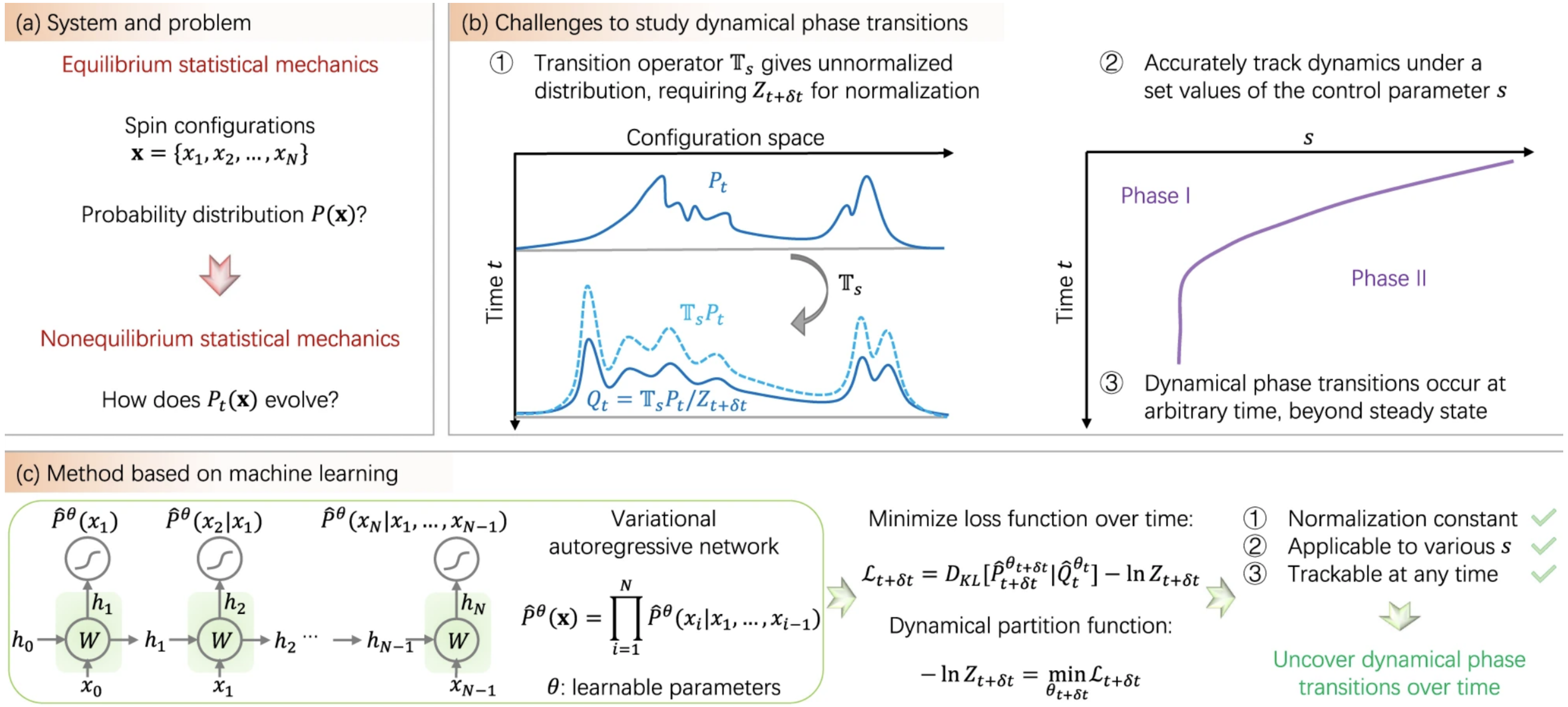
Learning nonequilibrium statistical mechanics and dynamical phase transitions

Ying Tang, Jing Liu, Jiang Zhang & Pan Zhang

Nature Communications **15**, Article number: 1117 (2024) | Cite this article

Abstract

Nonequilibrium statistical mechanics exhibit a variety of complex phenomena far from equilibrium. It inherits challenges of equilibrium, including accurately describing the joint distribution of a large number of configurations, and also poses new challenges as the distribution evolves over time. Characterizing dynamical phase transitions as an emergent behavior further requires tracking nonequilibrium systems under a control parameter. While a number of methods have been proposed, such as tensor networks for one-dimensional lattices, we lack a method for arbitrary time beyond the steady state and for higher



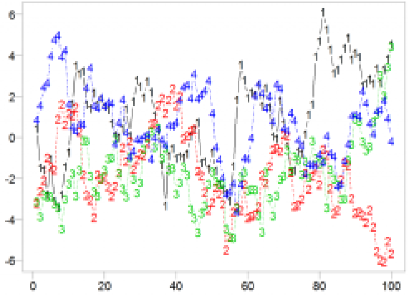
https://www.nature.com/articles/s41467-024-45172-8

Outline

- AI for complex systems
  - Complex Systems and Modelling Methods
  - Representation & Generation
  - Dynamics Learning
  - Network Reconstruction
  - Multi-scale Modelling
  - Simulation, optimization, and control
- Complexity science for AI

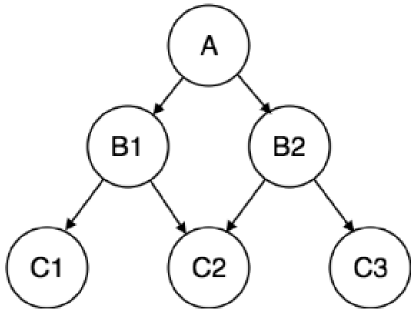
Problem Definition

Behavior (observations)



AI systems

Models



Predict Next Time Step

Takens's theorem

From Wikipedia, the free encyclopedia

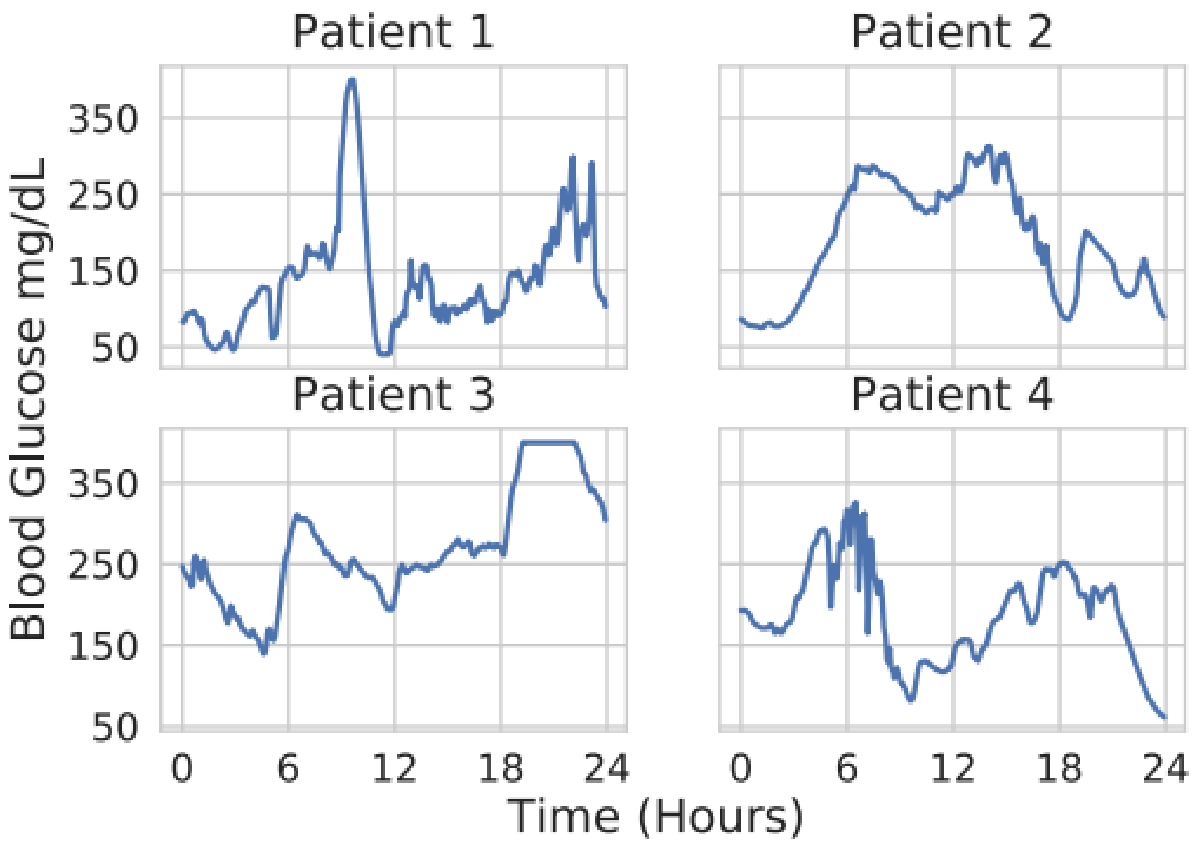
This article includes a list of general references, but **it lacks sufficient corresponding inline citations**. Please help to improve this article by introducing more precise citations. *(September 2020) (Learn how and when to remove this template message)*

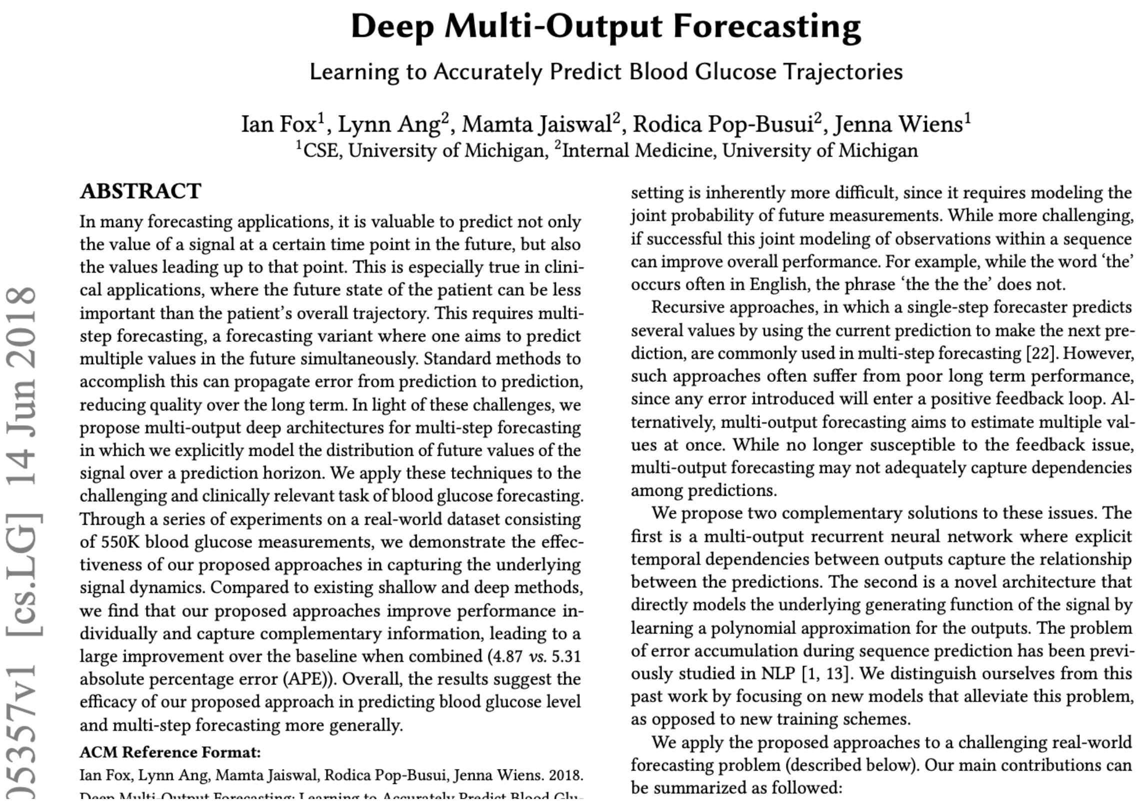
In the study of dynamical systems, a **delay embedding theorem** gives the conditions under which a chaotic dynamical system can be reconstructed from a sequence of observations of the state of a dynamical system. The reconstruction preserves the properties of the dynamical system that do not change under smooth coordinate changes (i.e., diffeomorphisms), but it does not preserve the geometric shape of structures in phase space.

- Abstractor reconstruction
- Polynomial regression
- Compressed sensing
- Driving response
- Reservoir Computing
- Time series analysis…

https://en.wikipedia.org/wiki/Takens's_theorem

RNN based Dynamics Learning





05357v1 [cs.LG] 14 Jun 2018

Deep Multi-Output Forecasting

Learning to Accurately Predict Blood Glucose Trajectories

Ian Fox[1], Lynn Ang[2], Mamta Jaiswal[2], Rodica Pop-Busui[2], Jenna Wiens[1]
[1]CSE, University of Michigan, [2]Internal Medicine, University of Michigan

ABSTRACT

In many forecasting applications, it is valuable to predict not only the value of a signal at a certain time point in the future, but also the values leading up to that point. This is especially true in clinical applications, where the future state of the patient can be less important than the patient's overall trajectory. This requires multi-step forecasting, a forecasting variant where one aims to predict multiple values in the future simultaneously. Standard methods to accomplish this can propagate error from prediction to prediction, reducing quality over the long term. In light of these challenges, we propose multi-output deep architectures for multi-step forecasting in which we explicitly model the distribution of future values of the signal over a prediction horizon. We apply these techniques to the challenging and clinically relevant task of blood glucose forecasting. Through a series of experiments on a real-world dataset consisting of 550K blood glucose measurements, we demonstrate the effectiveness of our proposed approaches in capturing the underlying signal dynamics. Compared to existing shallow and deep methods, we find that our proposed approaches improve performance individually and capture complementary information, leading to a large improvement over the baseline when combined (4.87 *vs.* 5.31 absolute percentage error (APE)). Overall, the results suggest the efficacy of our proposed approach in predicting blood glucose level and multi-step forecasting more generally.

ACM Reference Format:

Ian Fox, Lynn Ang, Mamta Jaiswal, Rodica Pop-Busui, Jenna Wiens. 2018. Deep Multi-Output Forecasting: Learning to Accurately Predict Blood Glu-

setting is inherently more difficult, since it requires modeling the joint probability of future measurements. While more challenging, if successful this joint modeling of observations within a sequence can improve overall performance. For example, while the word 'the' occurs often in English, the phrase 'the the the' does not.

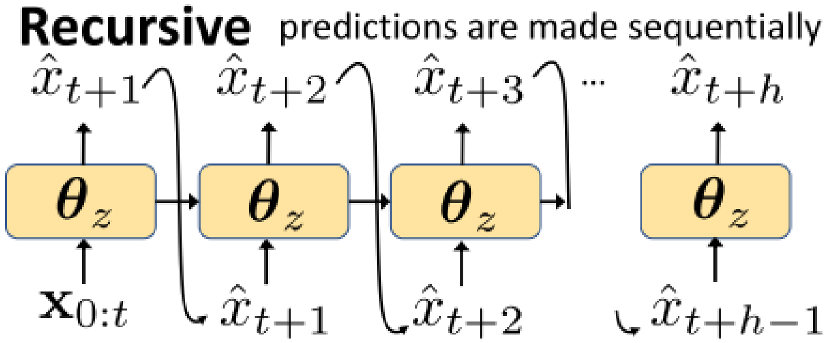
Recursive approaches, in which a single-step forecaster predicts several values by using the current prediction to make the next prediction, are commonly used in multi-step forecasting [22]. However, such approaches often suffer from poor long term performance, since any error introduced will enter a positive feedback loop. Alternatively, multi-output forecasting aims to estimate multiple values at once. While no longer susceptible to the feedback issue, multi-output forecasting may not adequately capture dependencies among predictions.

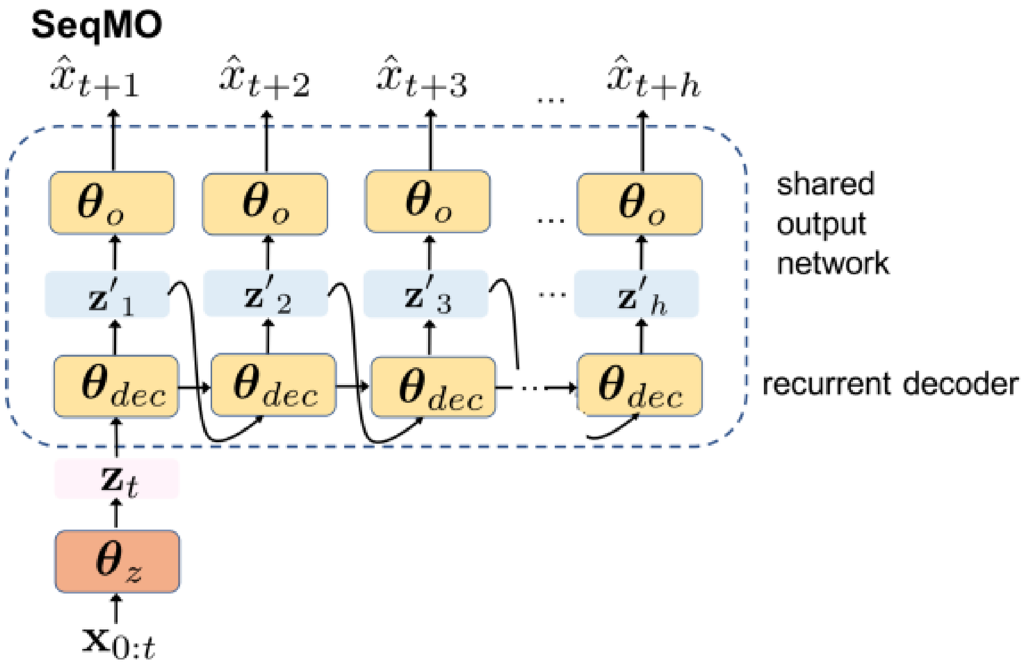
We propose two complementary solutions to these issues. The first is a multi-output recurrent neural network where explicit temporal dependencies between outputs capture the relationship between the predictions. The second is a novel architecture that directly models the underlying generating function of the signal by learning a polynomial approximation for the outputs. The problem of error accumulation during sequence prediction has been previously studied in NLP [1, 13]. We distinguish ourselves from this past work by focusing on new models that alleviate this problem, as opposed to new training schemes.

We apply the proposed approaches to a challenging real-world forecasting problem (described below). Our main contributions can be summarized as followed:

Ian Fox, Lynn Ang, Mamta Jaiswal, Rodica Pop-Busui, and Jenna Wiens. Deep multi-output forecasting: Learning to accurately predict blood glucose trajectories. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1387–1395. ACM, 2018.

Recursive v.s. Multi-output





Deep Multi-Output Forecasting

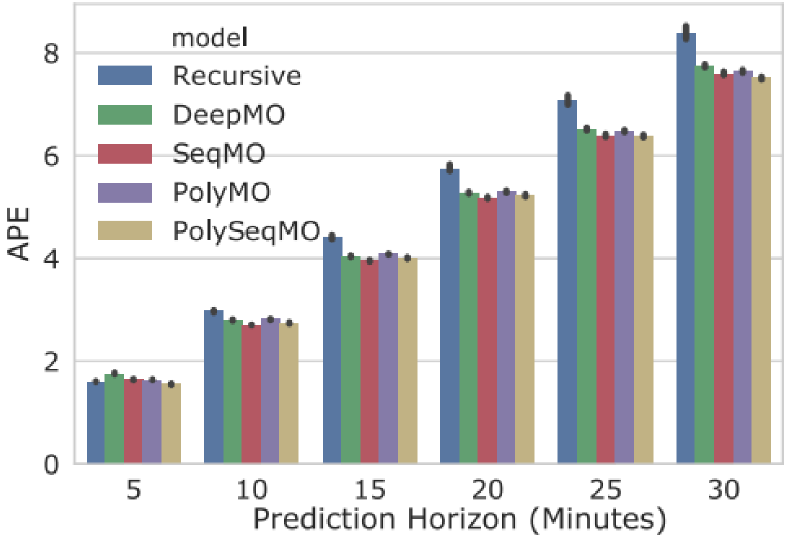
Learning to Accurately Predict Blood Glucose Trajectories

Ian Fox[1], Lynn Ang[2], Mamta Jaiswal[2], Rodica Pop-Busui[2], Jenna Wiens[1]
[1]CSE, University of Michigan, [2]Internal Medicine, University of Michigan

Forecasting with DeepMO involves transforming the input to a shared representation and then learning separate output networks for each time point in the prediction horizon h.

Ian Fox, Lynn Ang, Mamta Jaiswal, Rodica Pop-Busui, and Jenna Wiens. Deep multi-output forecasting: Learning to accurately predict blood glucose trajectories. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1387–1395. ACM, 2018.

Results



	Architecture	Full 39k	Event 3.1k	Hypo 1.2k	Hyper 1.9k
Shallow Baseline	Extrapolation	6.48 (0.21-42.12)	10.76 (1.42-63.98)	14.85 (1.89-86.81)	8.73 (1.30-36.87)
	RF: Rec	8.00 (0.62-40.83)	10.45 (1.99-65.21)	14.31 (2.73-91.12)	8.82 (1.85-30.42)
	RF: MO	5.18 (0.71-30.16)	10.64 (1.41-55.28)	17.88 (2.70-75.46)	8.20 (1.14-28.00)
Deep Baseline	Recursive	5.31 (0.00-29.32)	10.00 (1.45-46.22)	13.34 (2.17-62.86)	8.43 (1.24-30.49)
	DeepMO	5.01 (0.00-28.74)	9.93 (1.62-41.67)	12.91 (2.26-56.04)	8.52 (1.43-30.02)
Proposed	SeqMO	4.91 (0.00-28.95)	9.69 (1.51-41.54)	12.48 (2.28-54.02)	8.37 (1.29-29.46)
	PolyMO	4.95 (0.51-28.30)	9.79 (1.48-43.67)	12.49 (1.93-60.78)	8.46 (1.31-30.75)
	PolySeqMO	4.87 (0.48-27.80)	9.57 (1.43-43.59)	12.05 (2.03-60.90)	8.31 (1.24-29.76)
	PolySeqMO Ensemble	**4.59** (0.41-21.12)	**9.38** (1.35-42.34)	**11.61** (1.99-59.89)	**8.13** (1.18-29.49)

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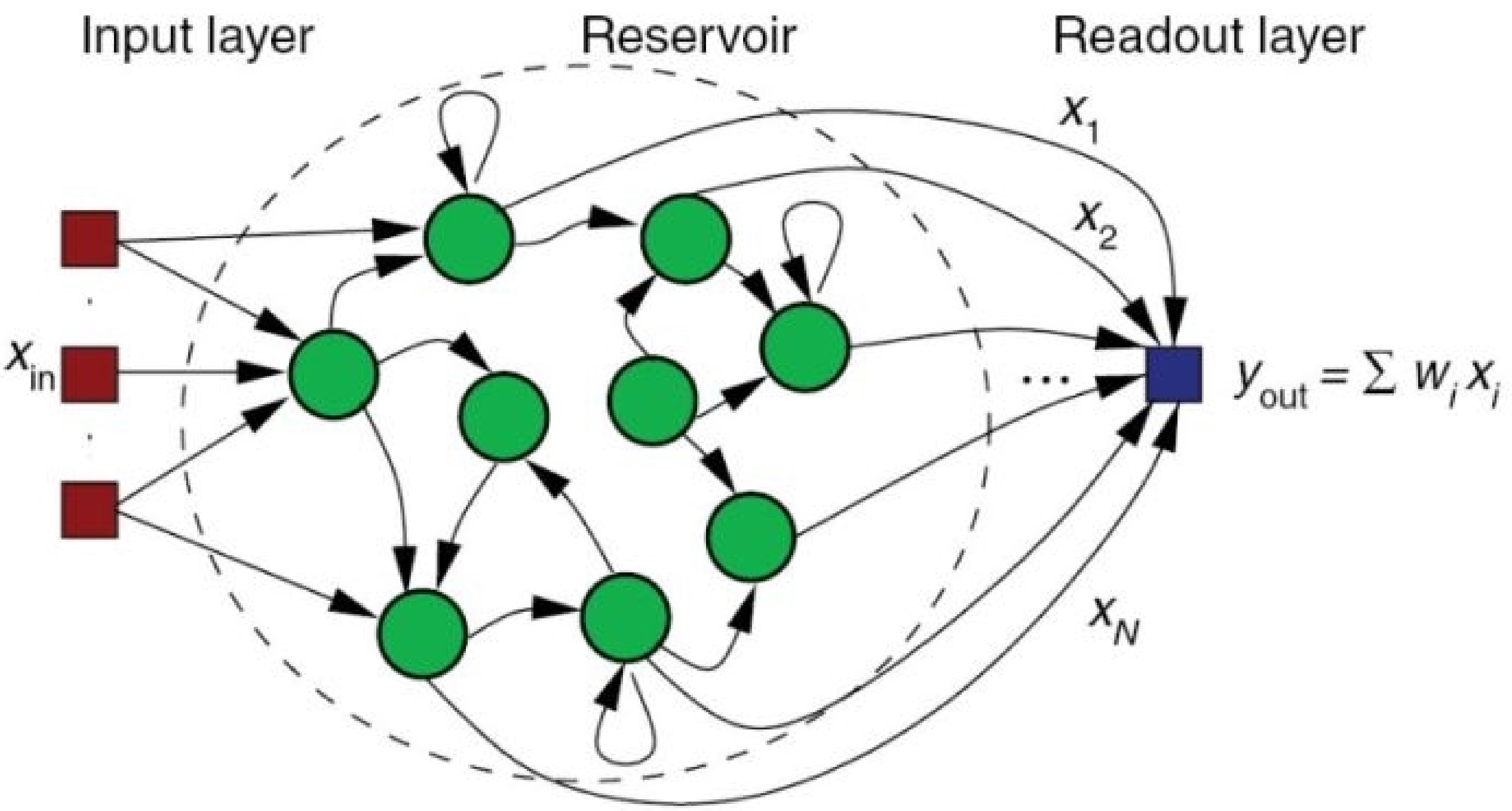
Reservoir Computing

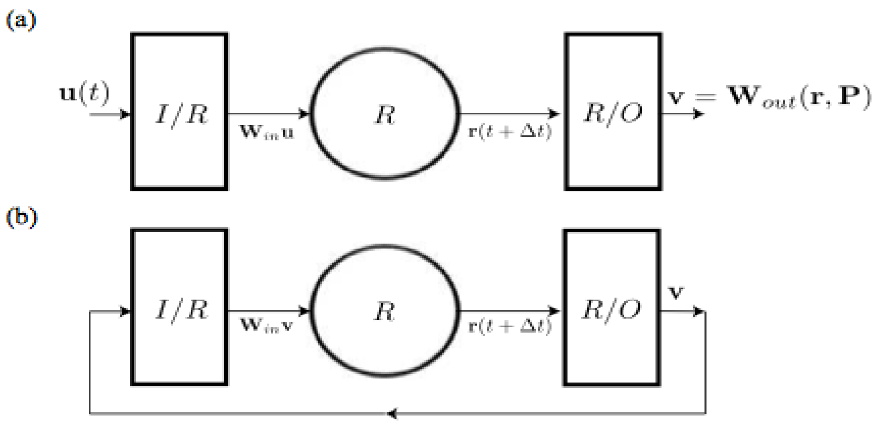


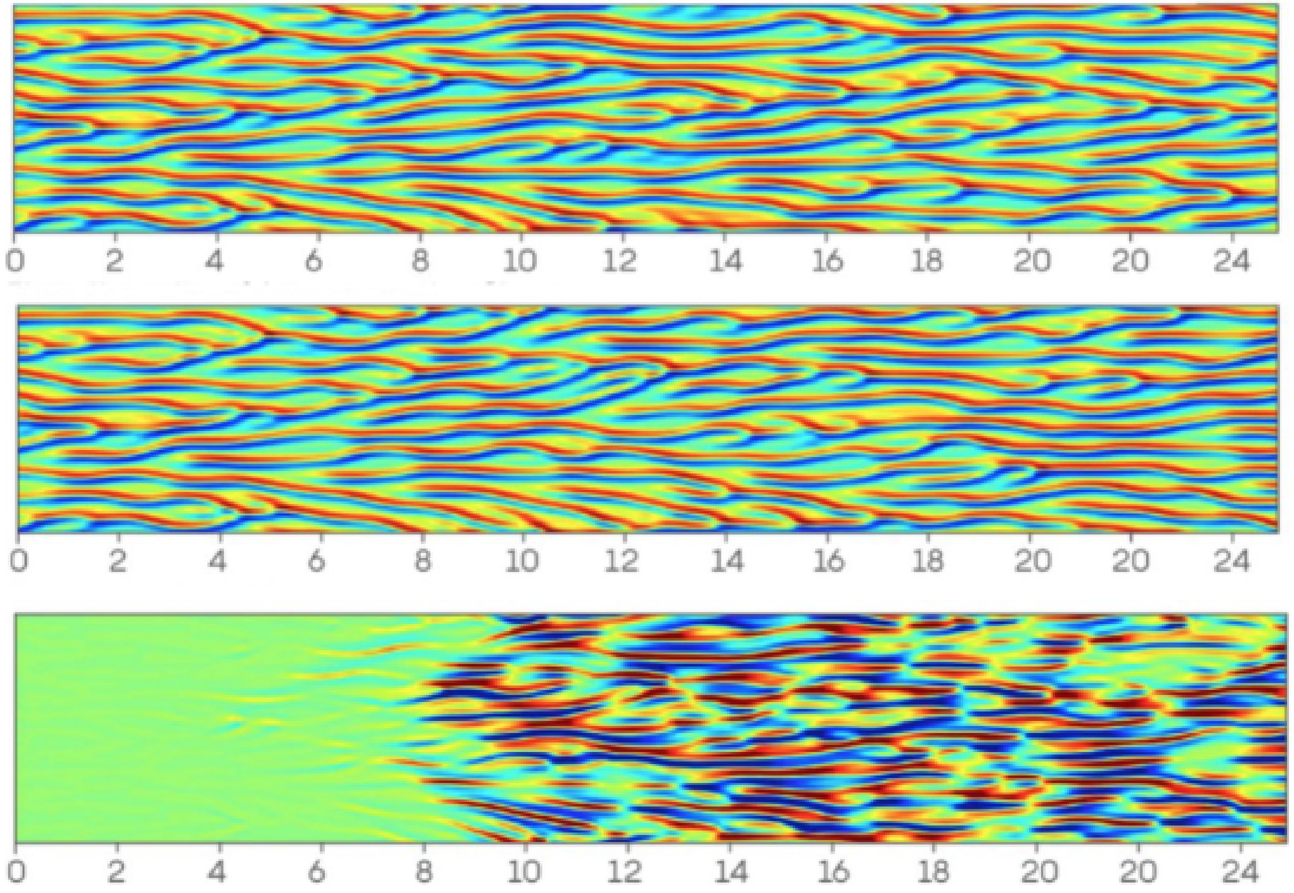
https://en.wikipedia.org/wiki/Reservoir_computing

Predict Chaotic Dynamics

Kuramoto-Sivashinsky equation:

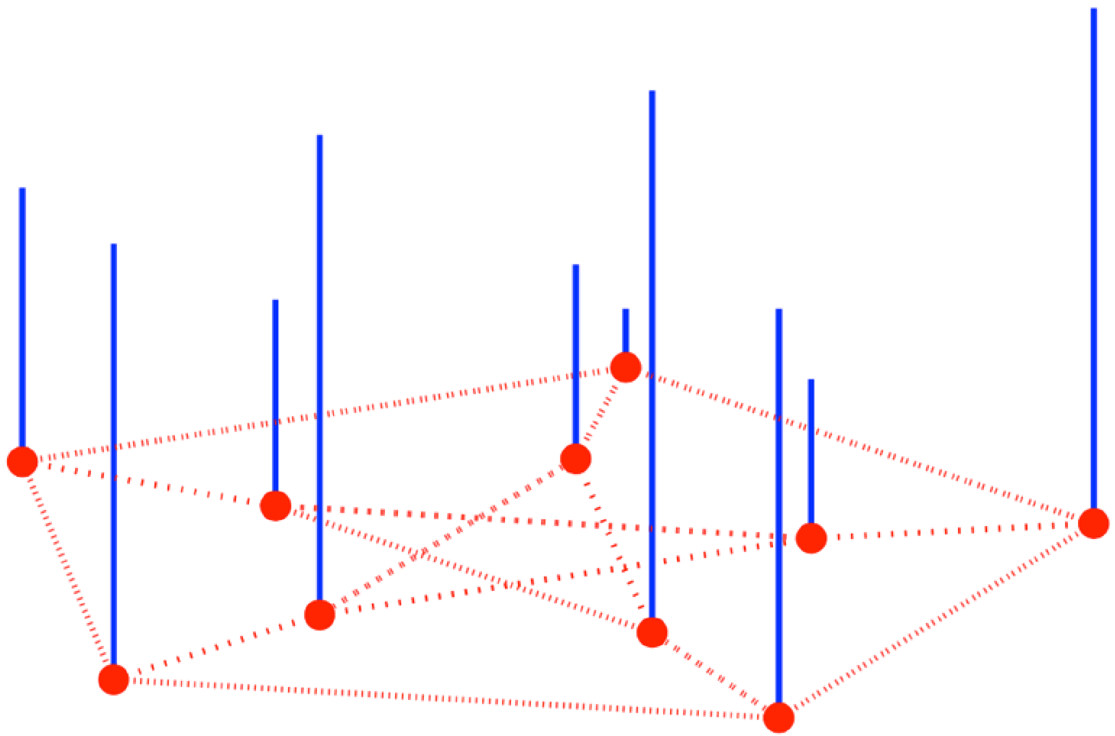
$$u_t + \nabla^4 u + \nabla^2 u + \frac{1}{2}|\nabla u|^2 = 0$$





Phys. Rev. Lett. 120, 024102

Dynamics on Graph

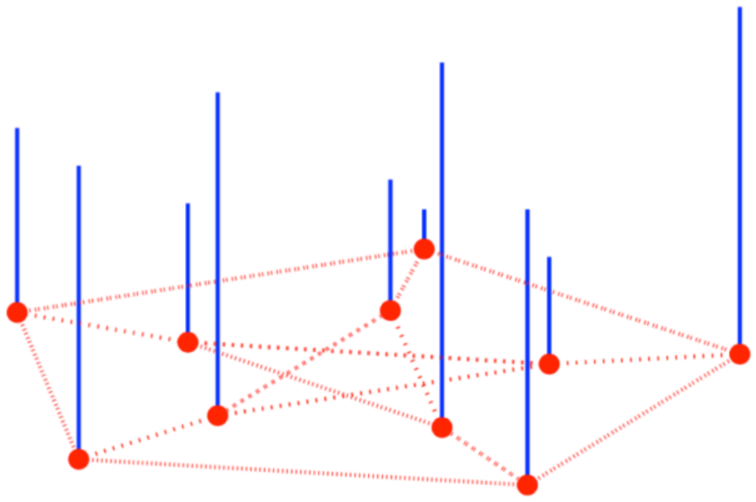


$$\frac{dX(t)}{dt} = f(X(t), A)$$

$$X(t) = (x_1(t), x_2(t), \dots, x_n(t))^T$$

$$X(t+1) = F(X(t), A)$$

Dynamics on Graph



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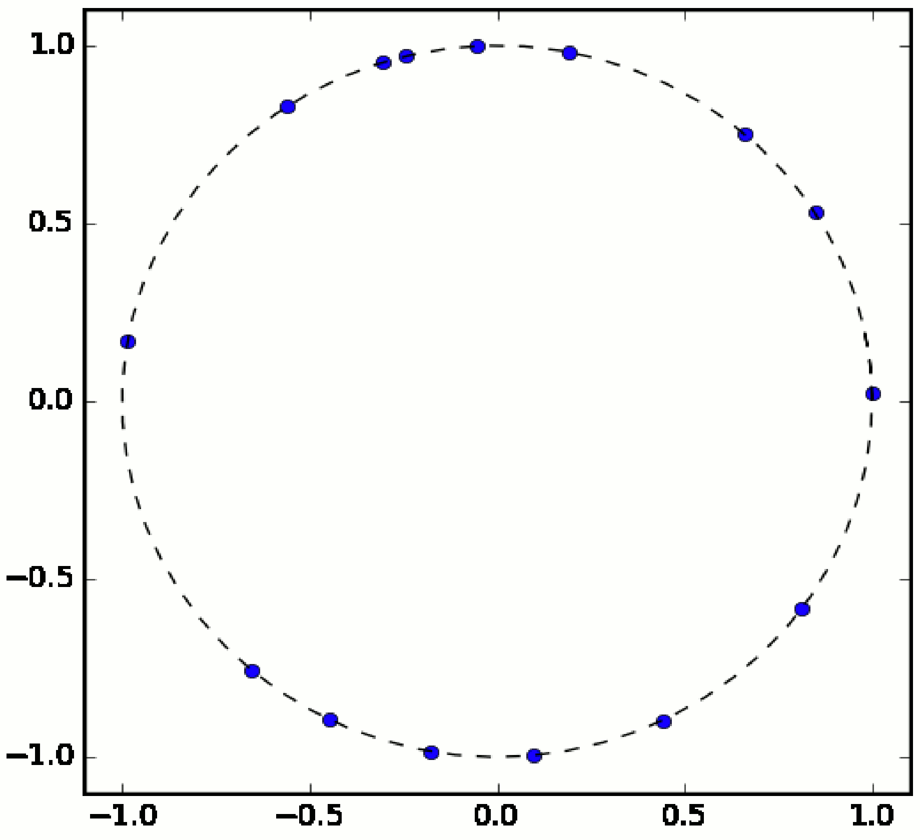

$$\frac{d\theta_i}{dt} = \omega_i + \frac{K}{N}\sum_{j=1}^{N}\sin(\theta_j - \theta_i), \qquad i = 1 \dots N,$$