NAVY Research Group
Department of Computer Science
Faculty of Electrical Engineering and Computer Science VŠB-TUO
17. listopadu 15
708 33 Ostrava-Poruba
Czech Republic

Bioinspired Computatin in Astrophysics

AIA 2019, ESO

Ivan Zelinka

MBCS CIPT, www.bcs.org/
http://www.springer.com/series/10624

Department of Computer Science
Faculty of Electrical Engineering and Computer Science, VŠB-TUO
17. listopadu 15 , 708 33 Ostrava-Poruba
Czech Republic
www.ivanzelinka.eu

Objectives

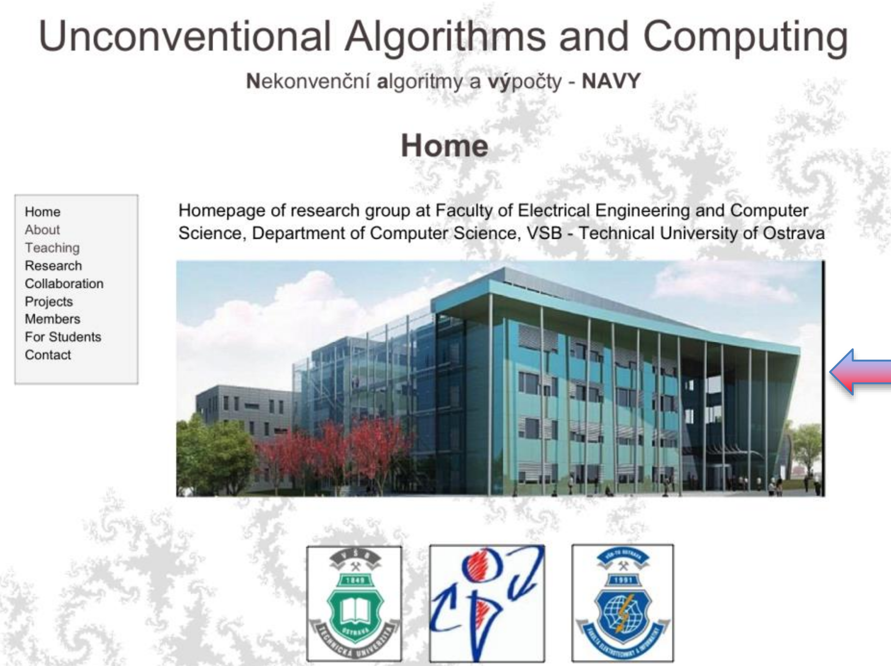
The objectives of the lesson are:

- Bioinspired vs unconventional algorithms
- Mutual relations
- Limits and benefits
- Examples
  - Solar activity prediction
  - Stellar data classification
- Special offer for AIA 2019

FEI VŠB-TU

http://www.vsb.cz/en/

NAVY
http://navy.cs.vsb.cz

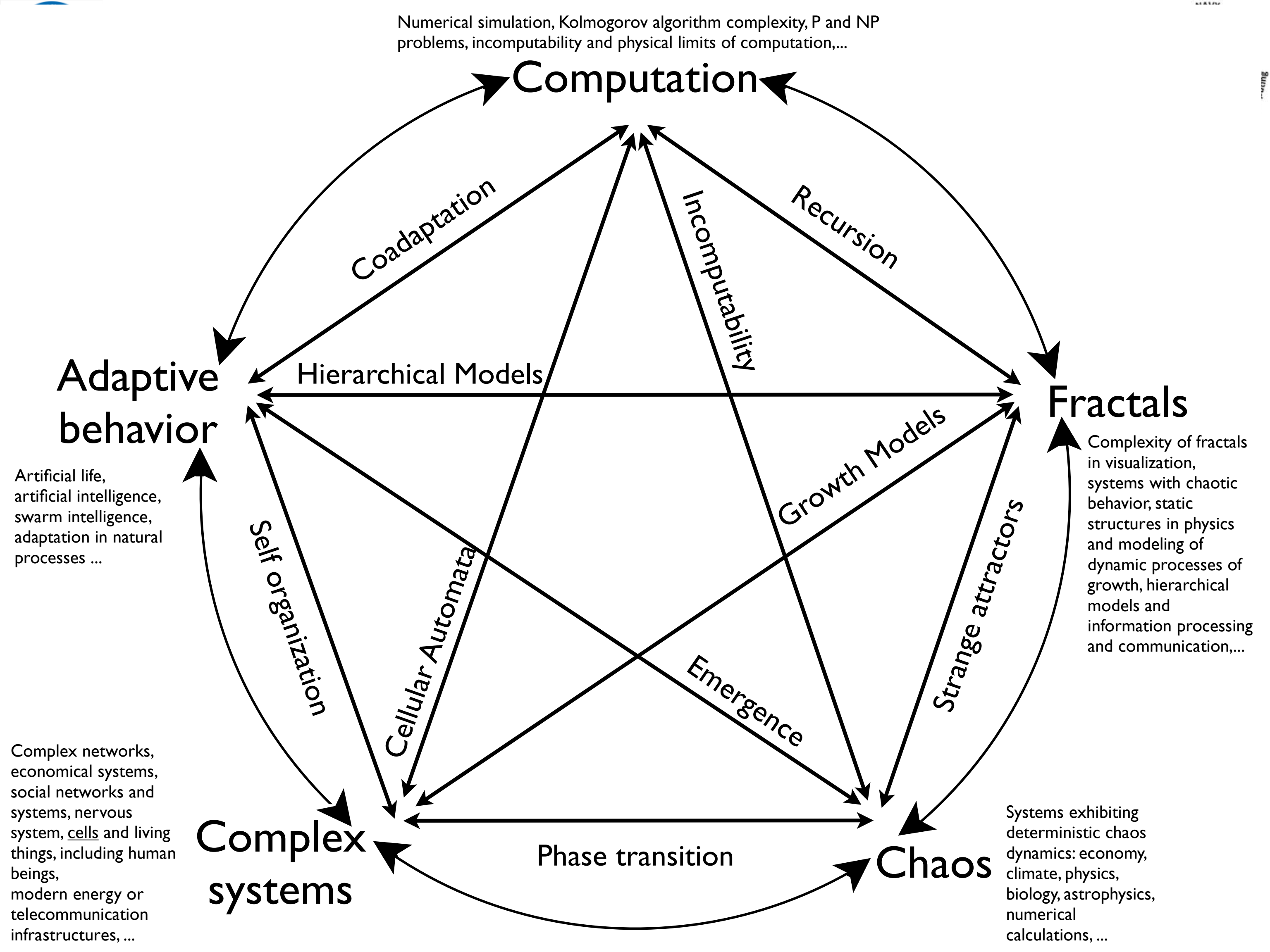


IT4Innovations
national
supercomputing
center

MUTUAL RELATIONS

General Introduction

- **Modern and unconventional computing methods**
  - **Artificial neural networks**
  - **Evolutions**
  - Deterministic chaos
  - Fractal geometry
  - Cellular automata
  - Fuzzy logic
  - Unconventional computation such as
    - Optical computing
    - Quantum computing
    - Chemical computing
    - DNA computing
    - Reversible computing
    - Game sourcing and **crowdsourcing**


Numerical simulation, Kolmogorov algorithm complexity, P and NP problems, incomputability and physical limits of computation,...
Computation
Coadaptation
Incomputability
Recursion
Adaptive behavior
Hierarchical Models
Fractals
Artificial life, artificial intelligence, swarm intelligence, adaptation in natural processes ...
Complexity of fractals in visualization, systems with chaotic behavior, static structures in physics and modeling of dynamic processes of growth, hierarchical models and information processing and communication,...
Growth Models
Self organization
Cellular Automata
Strange attractors
Emergence
Complex networks, economical systems, social networks and systems, nervous system, cells and living things, including human beings, modern energy or telecommunication infrastructures, ...
Complex systems
Phase transition
Chaos
Systems exhibiting deterministic chaos dynamics: economy, climate, physics, biology, astrophysics, numerical calculations, ...

Why AI in Astrophysics?

?????bytes scale?

- Robotic telescope (petabytes ?)
- Virtual Sky (exobytes ?)
- Kepler's law (guess ;))

Problems…

Why AI in Astrophysics?

Grand Challenge Problems in Computational Astrophysics

https://www.ipam.ucla.edu/programs/long-programs/grand-challenge-problems-in-computational-astrophysics/

The sophistication and the diversity of computational methods have grown alongside the power of computers, but there has emerged the perception amongst some theorists that we have reached certain roadblocks in this evolutionary process. While technical advances continue to be made, **including massive parallelization** and the development of dedicated special-purpose computers, such as GRAPE, **investigators have encountered various algorithmic limitations**. With the possible exception of some novel methodologies currently being explored, future progress in computational theory appears to be awaiting only the inexorable increase in raw computing power. The most advanced coding techniques, including adaptive mesh refinement (AMR), N-body tree codes, and smoothed particle hydrodynamics (SPH) and its offshoots, have been very successful**, but their accuracy in the 3-dimensional realm is often problematical, especially over long time spans**. The devil is often in the unresolved, small-scale details of such physical processes as turbulent cascades, turbulent energy dissipation, magnetic field line reconnection, narrow shock fronts and dynamical instabilities, among others.

A Peak of Research

- Tsang, B.T.H. and Schultz, W.C., 2019. **Deep Neural Network Classi**fier for Variable Stars with Novelty Detection Capability. *The Astrophysical Journal Letters*, *877*(2), p.L14.
- Shallue, C.J. and Vanderburg, A., 2018. **Identifying exoplanets with deep learning**: A five-planet resonant chain around kepler-80 and an eighth planet around kepler-90. *The Astronomical Journal*, *155*(2), p.94.
- Pearson, K.A., Palafox, L. and Griffith, C.A., 2017. **Searching for exoplanets using artificial intelligence**. *Monthly Notices of the Royal Astronomical Society*, *474*(1), pp.478-491.
- Silburt, A., Ali-Dib, M., Zhu, C., Jackson, A., Valencia, D., Kissin, Y., Tamayo, D. and Menou, K., 2019. **Lunar crater identification via deep learning.** *Icarus*, *317*, pp.27-38.
- Davies, A., Serjeant, S. and Bromley, J.M., 2019. **Using Convolutional Neural Networks to identify Gravitational Lenses in Astronomical im**ages. *Monthly Notices of the Royal Astronomical Society*.
- Lukic, V., Brüggen, M., Mingo, B., Croston, J.H., Kasieczka, G. and Best, P.N., 2019. Morphological **classification of radio galaxies: capsule networks versus convolutional neural networks**. *Monthly Notices of the Royal Astronomical Society*, *487*(2), pp.1729-1744.

ARE WE LIMITED IN COMPUTATION?

Search Space and its Complexity

Estimated Values of Some Functions

n / Function	10	50	100	300	1000
Polynomial					
5n	50	250	500	1500	5000
$n \log_2 n$	33	282	665	2469	9966
n^2	100	2 500	10 000	90 000	10^6 (7 digits)
n^3	1000	125 000	1×10^6 (7 digits)	27×10^6 (8 digits)	10^9 (10 digits)
Exponential					
2^n	1024	16 digit number	31 digit number	91 digit number	302 digit number
$n!$	$3{,}6\ 10^6$ (7 digits)	65 digit number	161digit number	623 digit number	Gigantic number
n^n	10×10^9 (11 digits)	85 digit number	201digit number	744 digit number	Gigantic number

For comparison, the number of protons in the visible universe has 79 digits.
Number of microseconds since the "big bang" has 24 digits.

Search Space and its Complexity

Estimated Values of Some Functions

n / Function	10	20	50	100	300
Polynomial					
n^2	1/10000 s	1/2500 s	1/400 s	1/100 s	9/100 s
n^5	1/10 s	3,2s	5,2s	2,8 hrs.	28,1 days
Exponential					
2^n	1/1000 s	1 s	35,7 years	400 x 10^{15} of centuries	75 digit No. of centuries
n^n	2,8 days	3,3 x 10^{15} of years	70 digit No. of centuries	185 digit No. of centuries	728 digit No. of centuries

Estimating the duration of *f*(*n*) operations if one takes about 1 microsecond.

Search Space and its Complexity

Estimated Values of Some Functions

	The maximum size of the input manageable in a reasonable time		
Function	**Current computers**	**100x faster computers**	**1000x faster computers**
n	N_1	$100\ N_1$	$1000\ N_1$
n^2	N_2	$10\ N_2$	$31{,}6\ N_2$
2^n	N_3	$N_3 + 6{,}64$	$N_3 + 9{,}97$
$n!$	N_4	$N_4 + 1$	$N_4 + 2$

Acceleration calculation using *n*-times faster computers.

Sources of Computational Limits

Selected sources of computational limits are

- Algorithm complexity and complexity of problems.
- Nonlinearities in computation and modeling.
- Mathematical limits - Gödel’s proof.
- Limits of “intelligent” computing.
- Thermodynamics.
- Quantum physics.

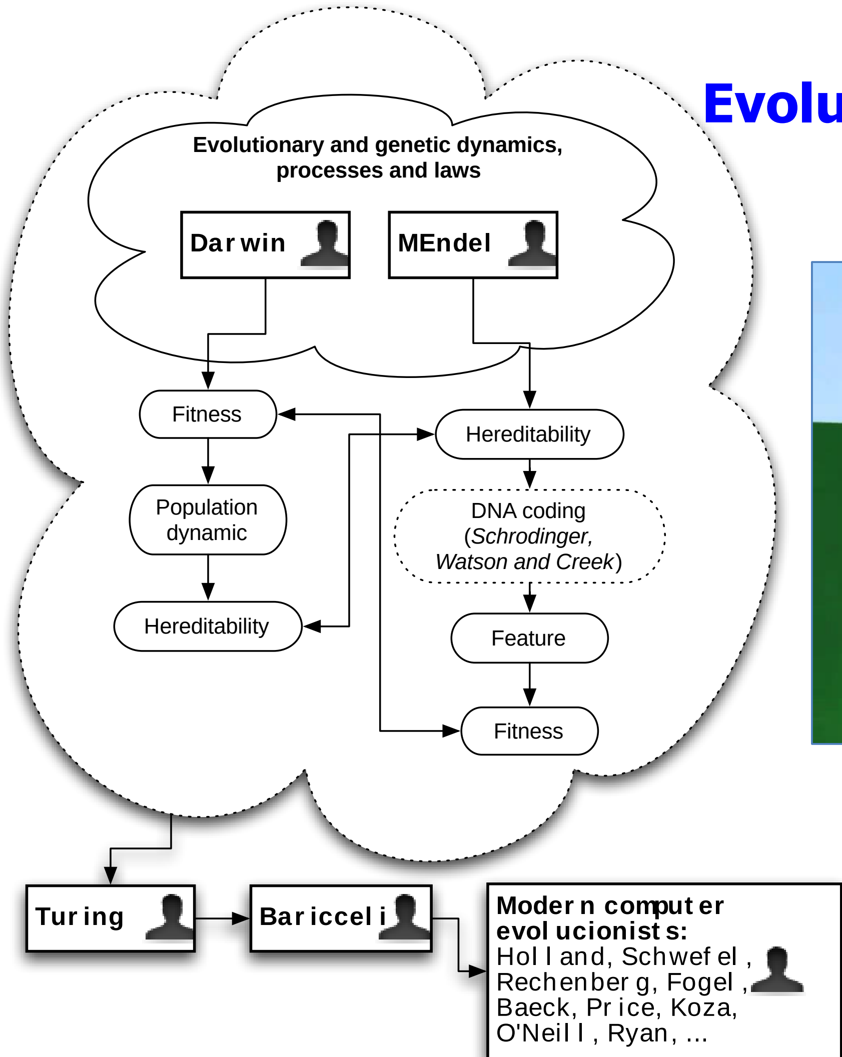
$$BL = 4\pi \frac{c^2}{h}$$

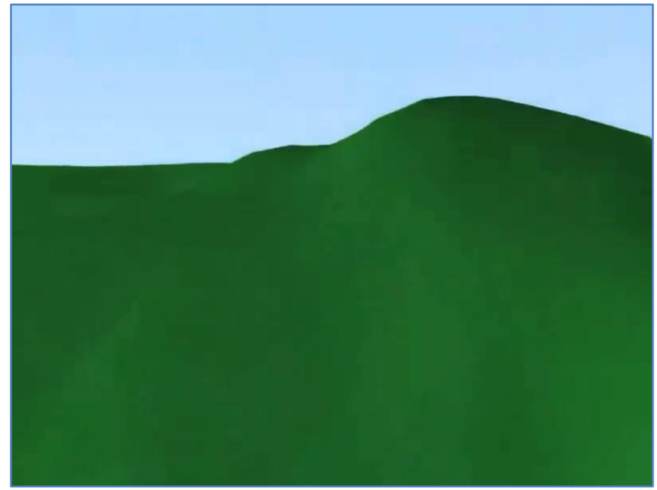
Bremermann’s limit that says how much of bits we can store/process in 1kg per second.

$$\boxed{BL \approx 1{,}7045 \cdot 10^{51}\ \mathrm{kg}^{-1} \cdot \mathrm{s}^{-1}.}$$

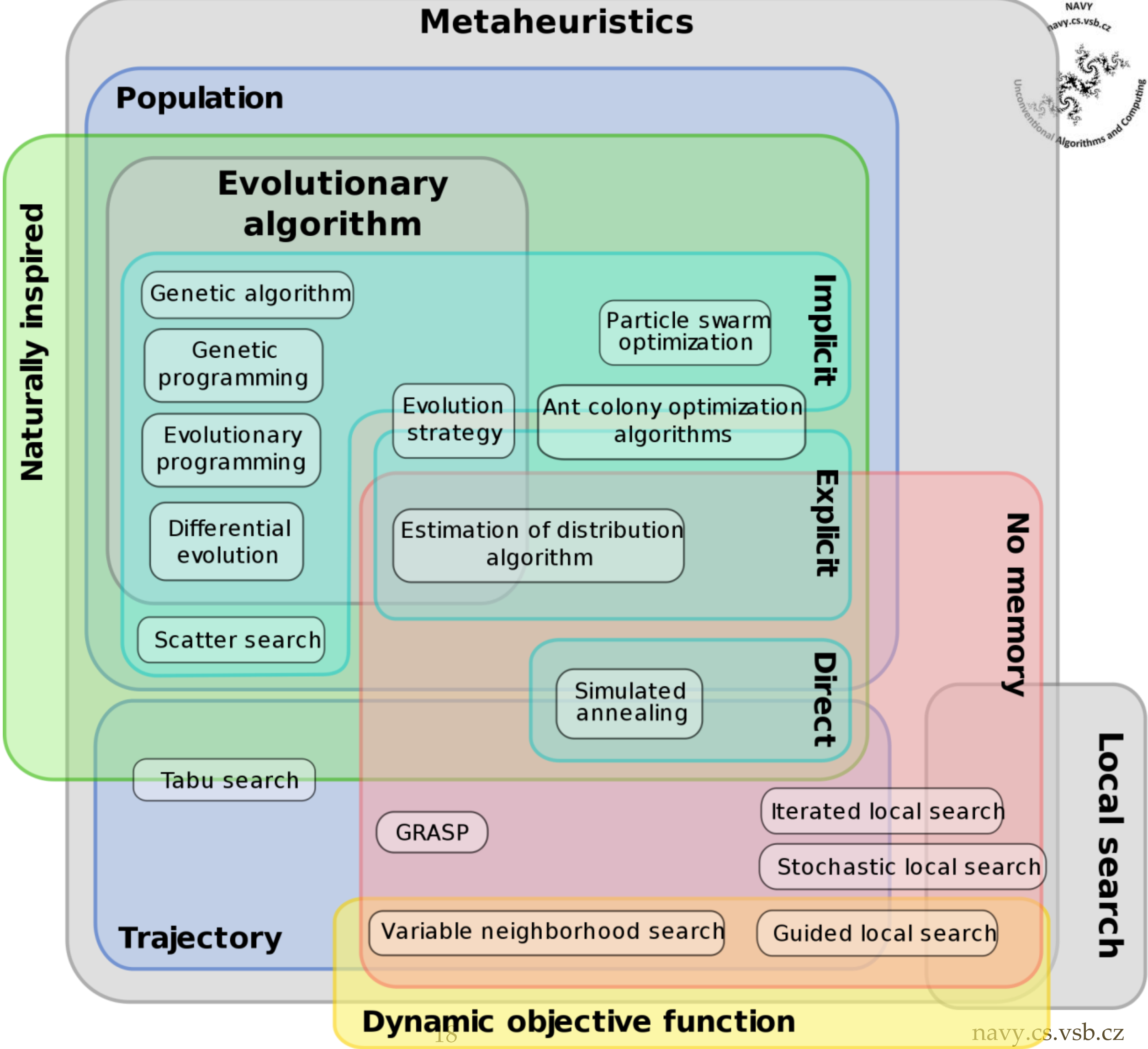
EVOLUTIONARY ALGORITHMS - A FEW BASIC FACTS…

Evolutionary algorithms





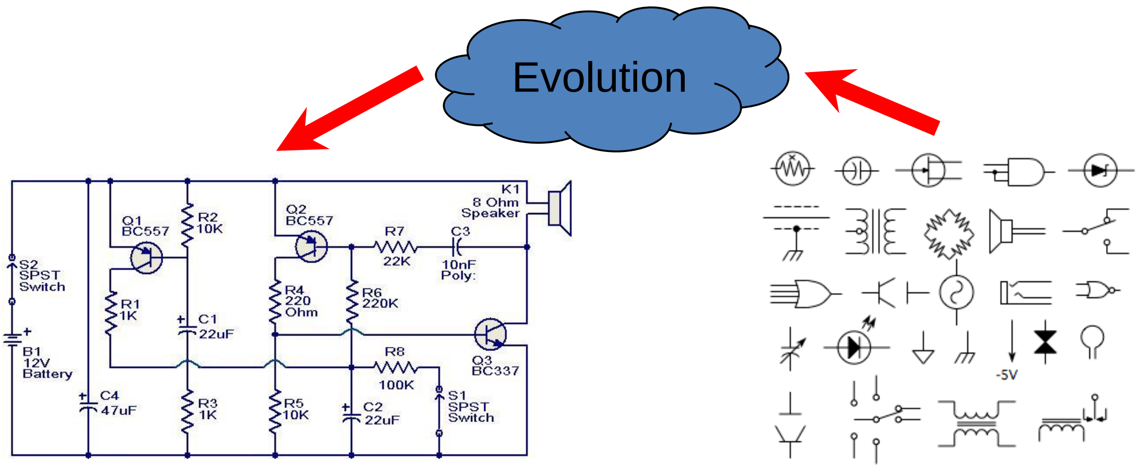
Nature Inspired Computation



Evolution of Symbolic Structures

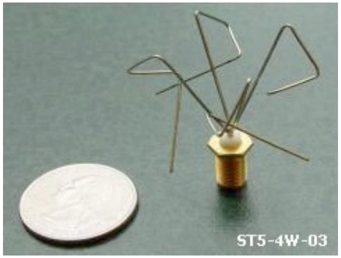
A Brief Overview

- Evolutionary manipulation with simple predefined objects essential for the synthesis of more complex structures which satisfy the predetermined conditions. As an example can be used electronic circuit.



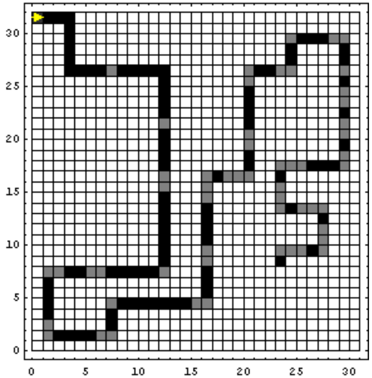
Evolution of Symbolic Structures

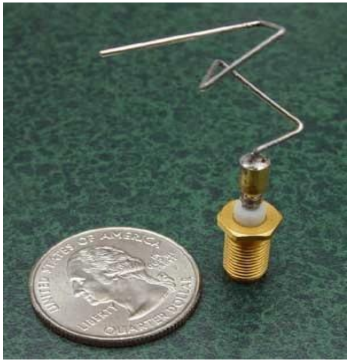
A Brief Overview



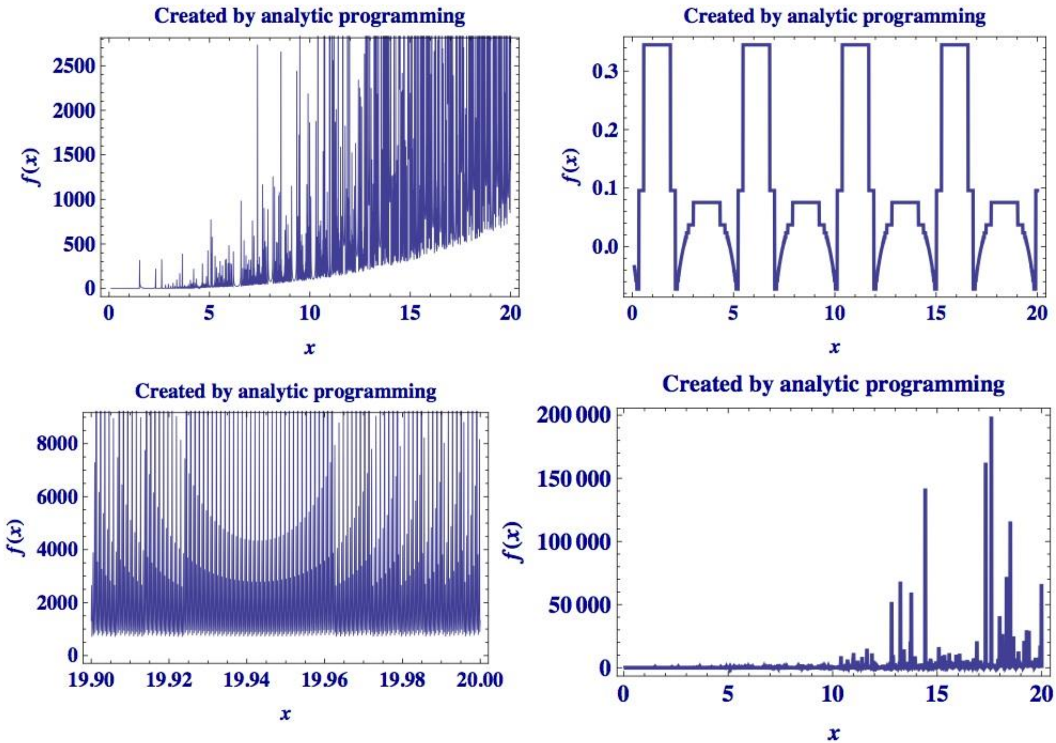
Examples:

- Robot control program.
- Antenna.
- Controller for feedback control.
- http://www.nelsonrobotics.org/evolutionary_robotics_web/links.html





Evolution of Symbolic Structures
Analytic Programming

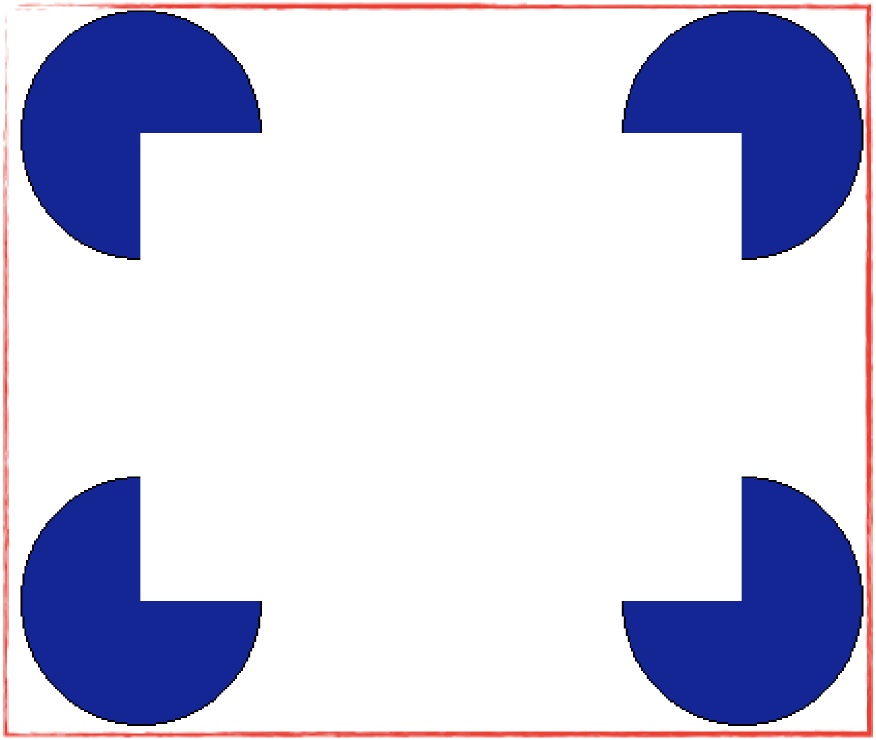


ANN -
A FEW BASIC FACTS...

Artificial Neural Networks

Our Perception

Are they really trustable? Lets test your neural network here…



Artificial Neural Networks

Our Perception

NN are able to process information and keep it. We call it memory. Lets demonstrate effect called memory switch.

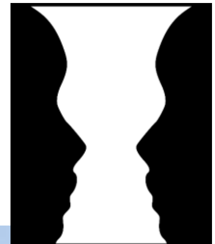
…

Is that benefit of NN or its drawback?

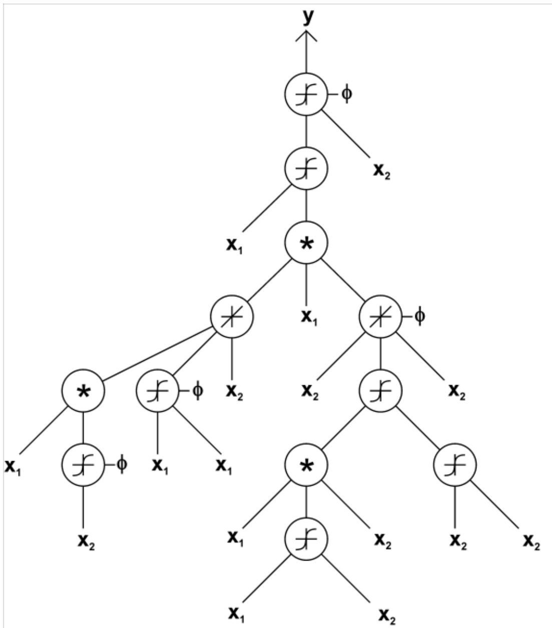
Wrong Classification ☺

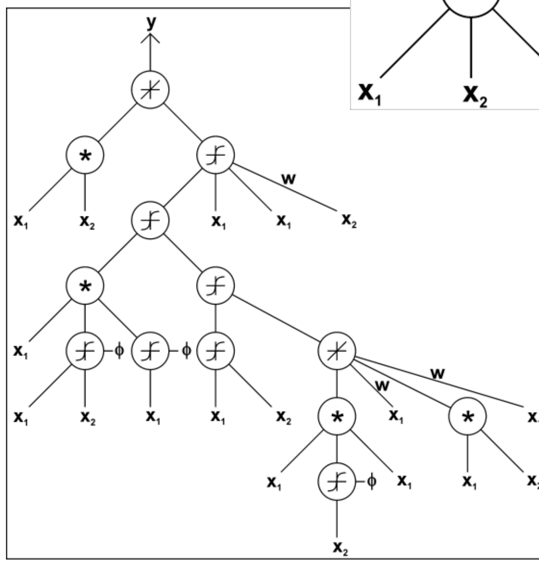
Artificial Neural Networks

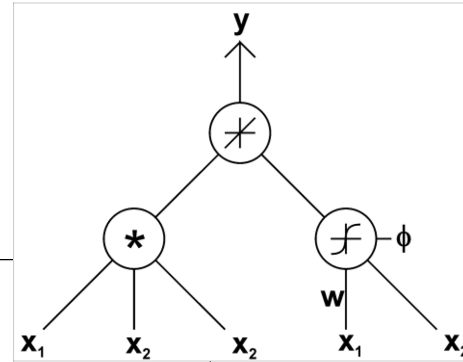
Our Perception



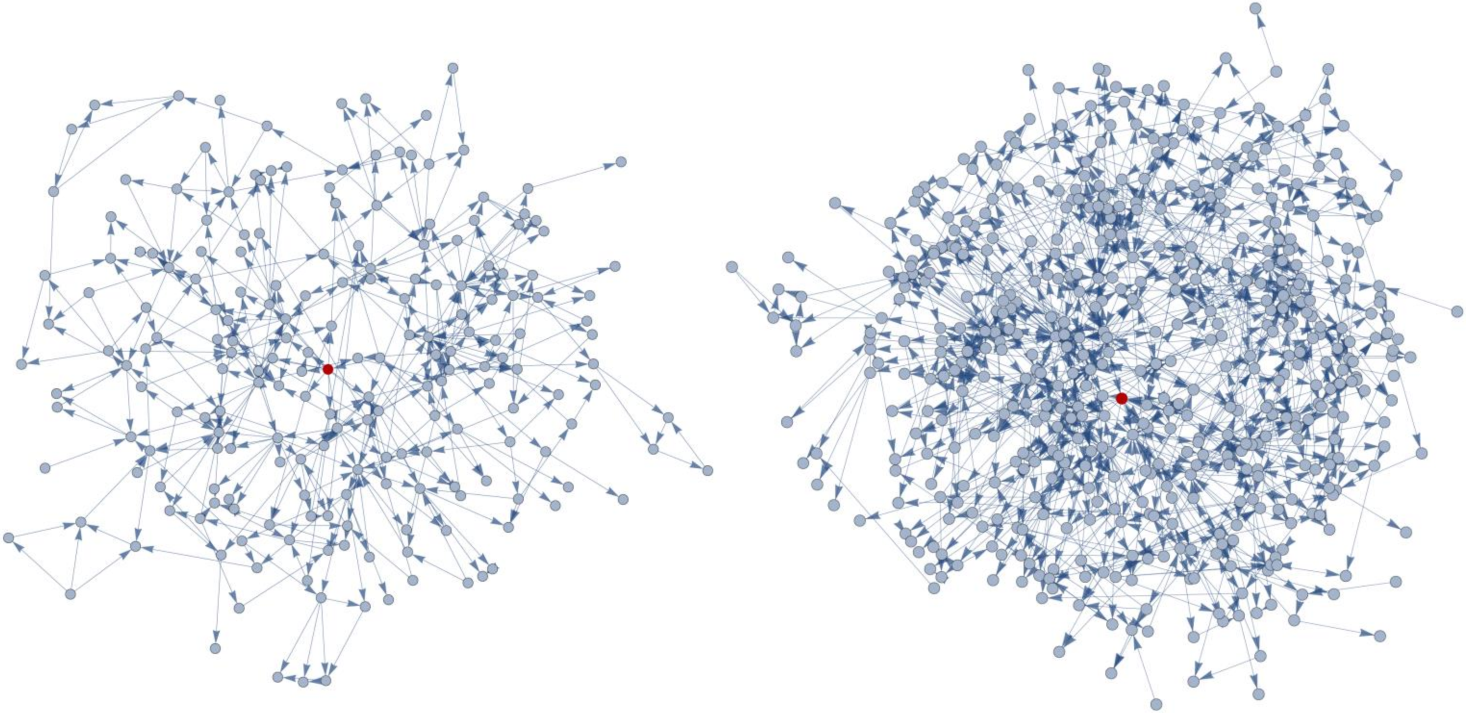
Artificial Neural Networks
Topology and Structure Optimization



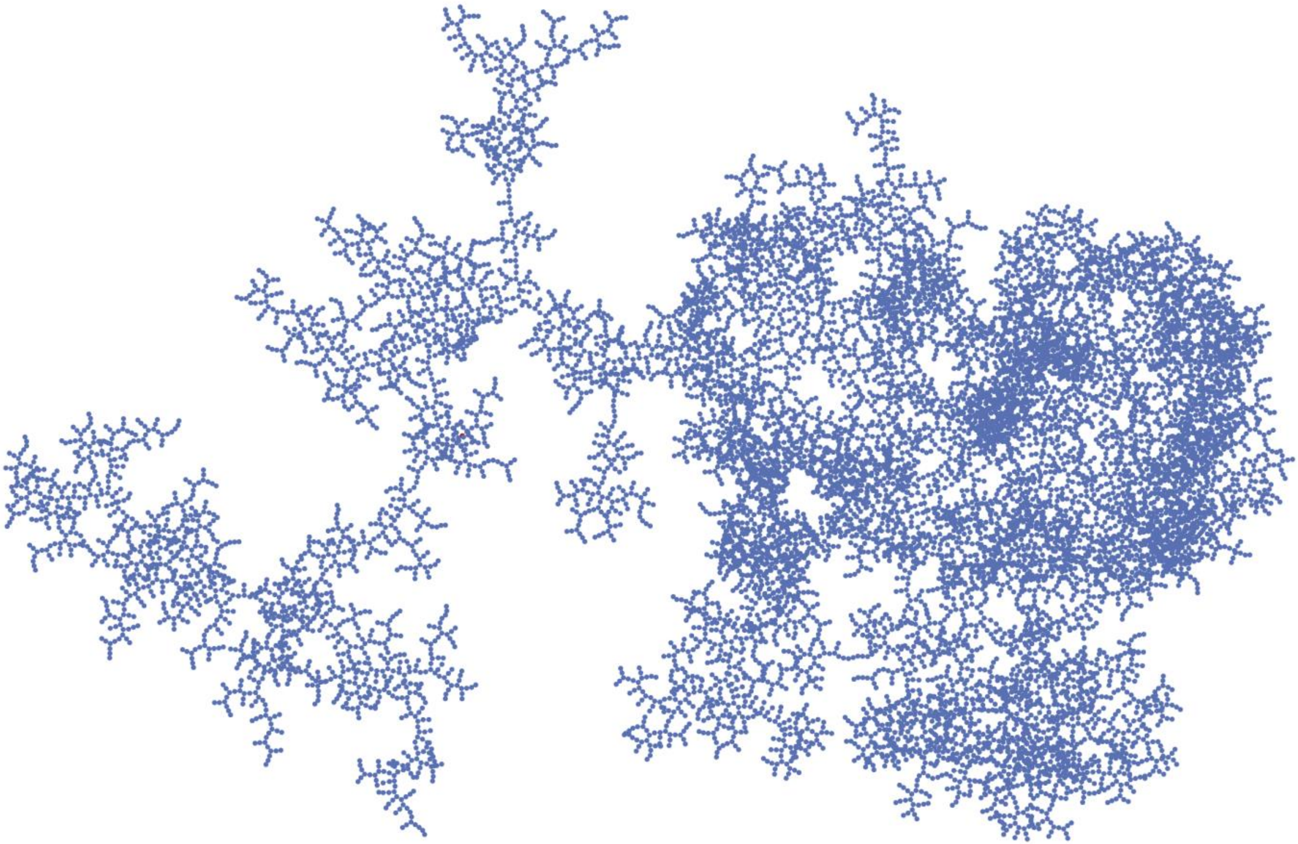




Artificial Neural Networks
Topology and Structure Optimization



Artificial Neural Networks
Topology and Structure Optimization



WHY BIOINSPIRED ALGORITMS?

Dizaster No. 11

WindUp - Hidden Oscillation - Attractors

Evolutionary Design of ET

Optimization in Astrophysics

Introduction to optimization with applications in astronomy and astrophysics

Stéphane Canu, Rémi Flamary, David Mary

July 18, 2016

Abstract

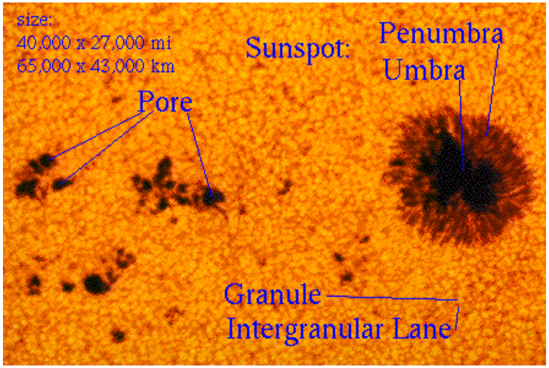
This chapter aims at providing an introduction to numerical optimization with some applications in astronomy and astrophysics. We provide important preliminary definitions that will guide the reader towards different optimization procedures. We discuss three families of optimization problems and describe numerical algorithms allowing, when this is possible, to solve these problems. For each family, we present in detail simple examples and more involved advanced examples. As a final illustration, we focus on two worked-out examples of optimization applied to astronomical data. The first application is a supervised classification of RR-Lyrae stars. The second one is the denoising of galactic spectra formulated by means of sparsity inducing models in a redundant dictionary.

Canu, S., Flamary, R. and Mary, D., 2016. Introduction to optimization with applications in astronomy and astrophysics. *EAS Publications Series*, *78*, pp.127-161.

EXAMPLES

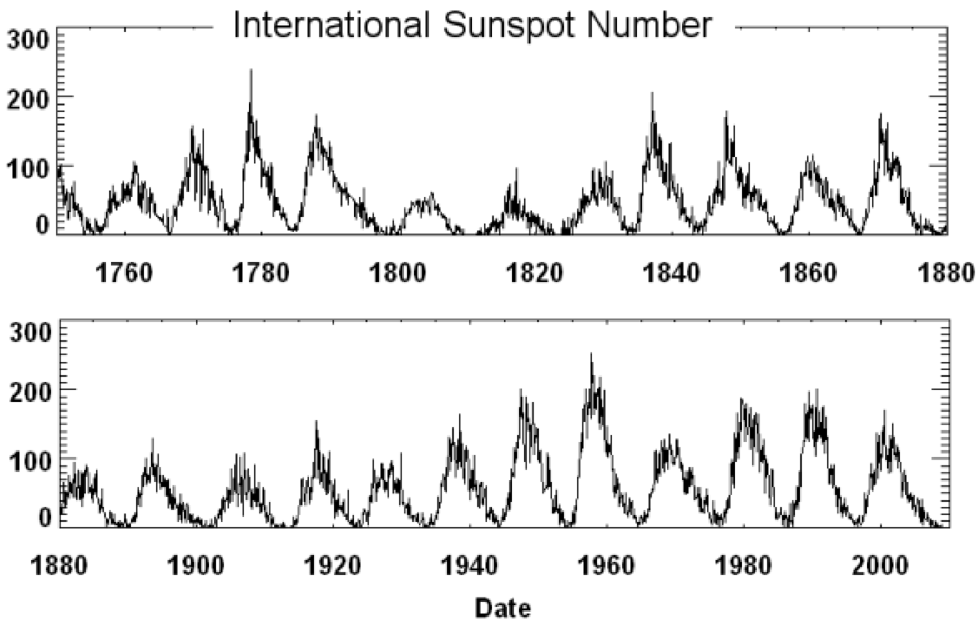
Artificial Neural Networks
On ANN Use – Prediction

- The prediction is based on the use of various mathematical algorithms. Its goal is to accurately predict the future state of the dynamic system based on the current state. the history of its behavior and its mathematical model.
- Prediction of the Sun activity
  - The Sun activity. importance and impact
  - Periodicity
  - Wolf (sunspot) number



Artificial Neural Networks
On ANN Use – Prediction

- Prediction of the Sun activity
  - Graph



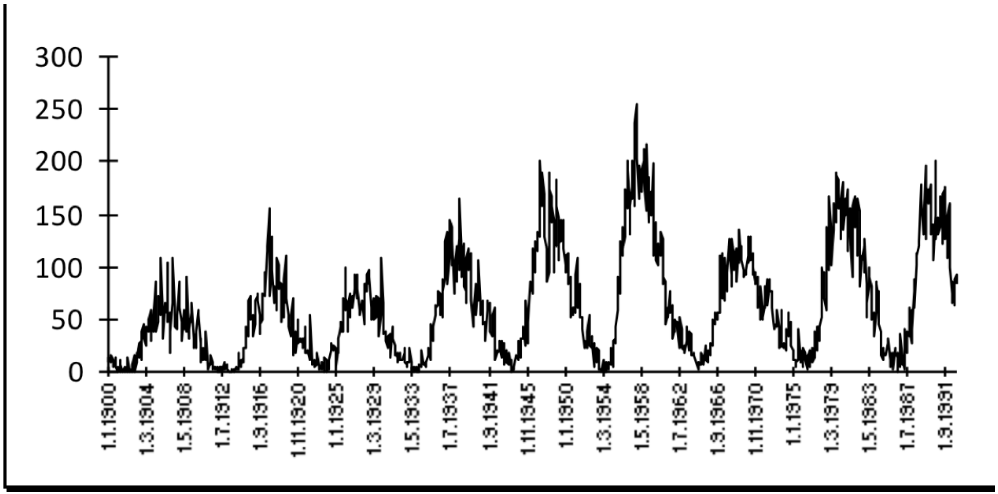
Artificial Neural Networks
On ANN Use – Prediction

- Single-value prediction
- Multiple-value prediction
- Prediction of the Sun activity
  - Training set preparation
    - Interval
    - Shift
    - Prediction window

Artificial Neural Networks
On ANN Use – Prediction

- Prediction of the Sun activity
  - Data smoothing

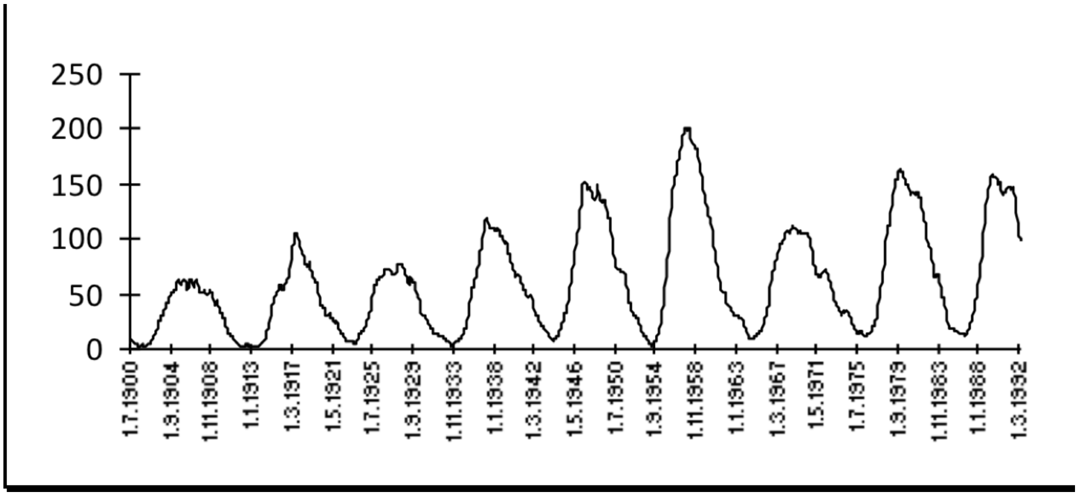
$$A_{smooth} = T_{-6} + T_{+6} + \frac{2\sum_{i=T-5}^{i=T+5} T_i}{24}$$



Artificial Neural Networks
On ANN Use – Prediction

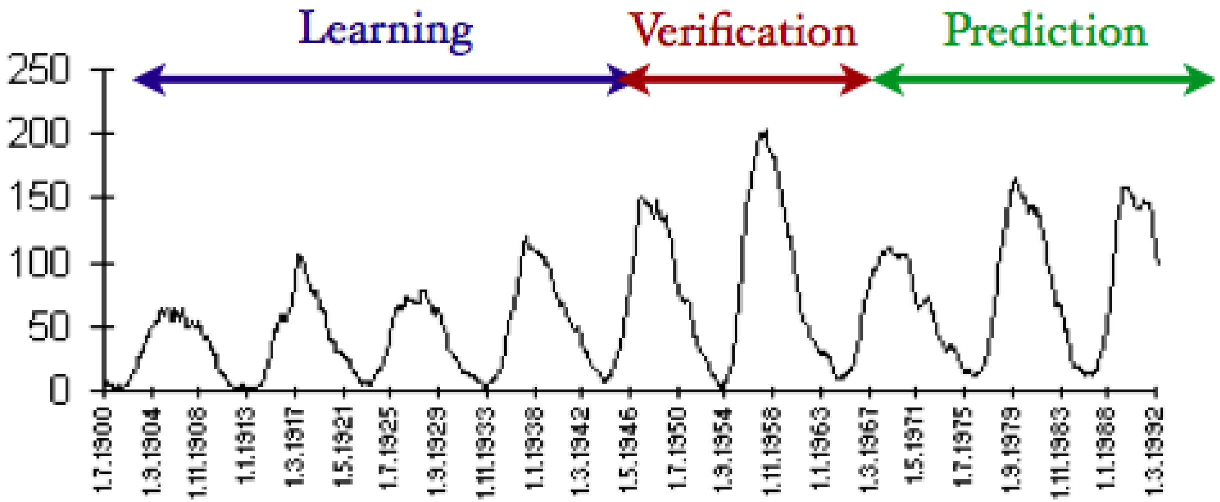
- Prediction of the Sun activity
  - Data smoothing

$$A_{smooth} = T_{-6} + T_{+6} + \frac{2\sum_{i=T-5}^{i=T+5} T_i}{24}$$



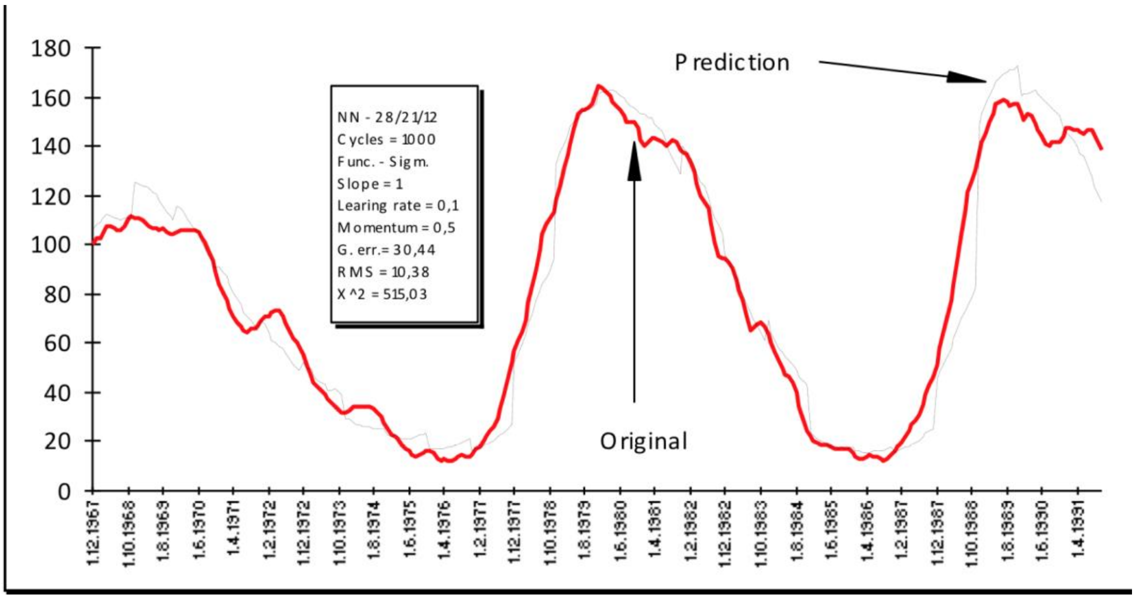
Artificial Neural Networks
On ANN Use – Prediction

- Prediction of the Sun activity

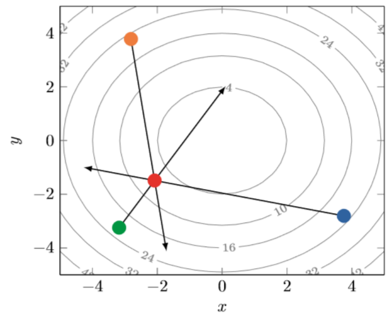


Artificial Neural Networks
On ANN Use – Prediction

- Prediction of the Sun activity



Evolutionary Synthesis of Automatic Classification on Astroinformatic Big Data



$$\text{Input set} = \{1, 3, 4, 4, 5, 7\}$$

m1 m3 m5

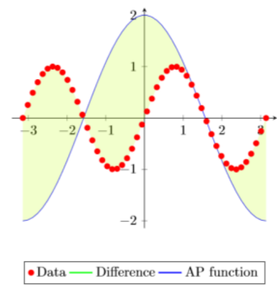
m2 m4

$$\Rightarrow \quad sin(tan(\pi)) + tan(t)$$

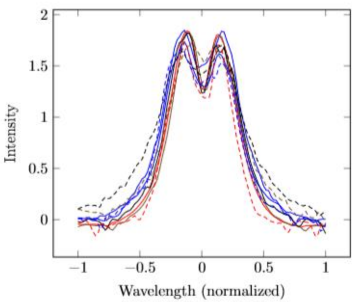
$$\text{GFS} = \{+, /, sin, tan, t, 0.5, \pi\}$$

m1 m3 m5

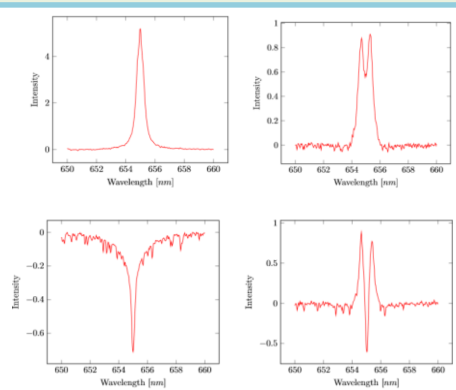
m2 m4



Evolutionary algorithms + symbolic regression = synthesized function that fit data



Synthesized models are then compared and used to classify astrophysical data



Four kind of spectra to be used for classification are processed by symbolic regression

Kojecky, L., Zelinka, I., Prasad, A., Vantuch, T. and Tomaszek, L., 2018. Investigation on unconventional synthesis of astroinformatic data classifier powered by irregular dynamics. *IEEE Intelligent Systems*, *33*(4), pp.63-77.

Evolutionary Synthesis of Automatic Classification on Astroinformatic Big Data

$$\frac{x + \left(\frac{\frac{60.05}{92.76} - x \cdot x}{x} \cdot x - (x - (x - 34.92))\right)}{(x - 5.77) + \left(\left(\frac{x - 109.38}{-\frac{41.27}{58.51}} + \frac{-259.33 \cdot x}{x}\right) - x \cdot (64.28 \cdot x \cdot 2.69)\right) + (x \cdot x)}$$

$$\frac{-x^2 + x - 34.2726}{-172.913x^4 - 1.41774x^3 - 104.258x^2 + x - 5.77}$$

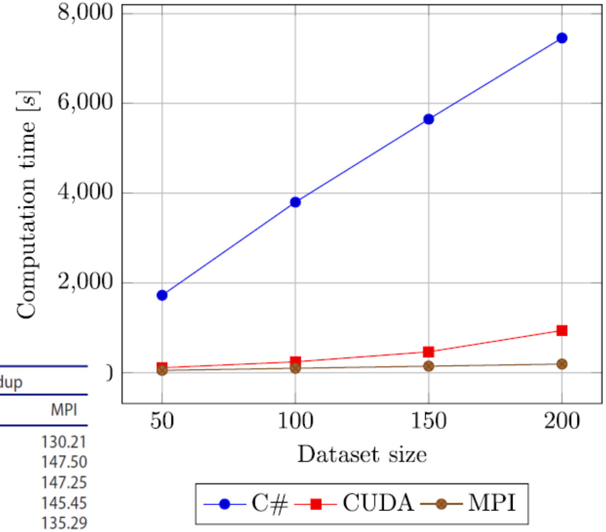


Table 7. Simulation results of basic AP.

		Time			Speedup	
Dataset	Time	C#	CUDA	MPI	CUDA	MPI
50	Max	18.23	0.41	0.14	44.46	130.21
	Med	17.70	0.29	0.12	61.03	147.50
	Avg	17.67	0.30	0.12	58.90	147.25
	Min	16.99	0.29	0.11	58.59	145.45
100	Max	28.41	1.31	0.21	21.69	135.29
	Med	24.56	0.63	0.19	38.98	129.26
	Avg	24.80	0.64	0.19	38.75	130.53
	Min	22.83	0.62	0.17	36.82	134.29
150	Max	33.34	1.81	0.28	18.42	119.07
	Med	31.55	1.31	0.26	24.08	121.35
	Avg	31.41	1.32	0.26	23.80	120.81
	Min	29.29	1.30	0.25	22.53	117.16
200	Max	39.32	2.72	0.37	14.46	106.27
	Med	36.11	2.13	0.33	16.95	109.42
	Avg	36.37	2.14	0.33	17.00	110.21
	Min	34.82	2.12	0.29	16.42	120.07

Kojecky, L., Zelinka, I., Prasad, A., Vantuch, T. and Tomaszek, L., 2018. Investigation on unconventional synthesis of astroinformatic data classifier powered by irregular dynamics. *IEEE Intelligent Systems*, *33*(4), pp.63-77.

Evolutionary Synthesis of Automatic Classification on Astroinformatic Big Data

Table 5. Total percentage of successfully classified spectra using original SOMA settings.

Class	Correct	Incorrect	Rate [%]
1	170	7	96.0
2	150	22	87.2
3	1089	70	94.0
4	55	1	98.2

Table 6. Total percentage of successfully classified spectra using extended SOMA settings.

Class	Correct	Incorrect	Rate [%]
1	172	5	97.2
2	159	13	92.4
3	1157	2	99.8
4	55	1	98.2

Kojecky, L., Zelinka, I., Prasad, A., Vantuch, T. and Tomaszek, L., 2018. Investigation on unconventional synthesis of astroinformatic data classifier powered by irregular dynamics. *IEEE Intelligent Systems*, *33*(4), pp.63-77.

Evolutionary Synthesis of Automatic Classification on Astroinformatic Big Data

TABLE 2
The classification results

		Actual class 1	2	3	4	Success [%]
Predicted class using classic PRNG	1	172	13	0	0	97.2
	2	5	157	0	0	91.3
	3	0	0	1134	1	97.8
	4	0	2	25	55	98.2
Predicted class using Mersenne Twister	1	172	13	0	0	97.2
	2	5	153	0	0	89.0
	3	0	0	1128	1	97.3
	4	0	6	31	55	98.2
Predicted class using Logistic map	1	170	14	0	0	96.0
	2	7	153	0	0	89.0
	3	0	0	1130	1	97.5
	4	0	5	29	55	98.2
Predicted class using SNA with Settings 1	1	167	13	0	0	94.4
	2	10	156	0	0	90.7
	3	0	0	1124	1	97.0
	4	0	3	35	55	98.2
Predicted class	1	173	14	0	0	97.7

TABLE 3
The classification results of classical methods

		Actual class 1	2	3	4	Success [%]
Predicted class using RF	1	177	4	0	0	100
	2	0	163	0	0	94.8
	3	0	5	1159	12	100
	4	0	0	0	44	78.6
Predicted class using SVC	1	177	3	0	0	100
	2	0	163	0	0	94.8
	3	0	6	1159	7	100
	4	0	0	0	49	87.5
Predicted class using kNN	1	177	4	0	0	100
	2	0	163	0	0	95.3
	3	0	4	1159	8	100
	4	0	0	0	48	85.7
Predicted class using MLP	1	177	4	0	0	100
	2	0	163	0	0	95.3
	3	0	4	1159	4	100
	4	0	6	0	52	92.8

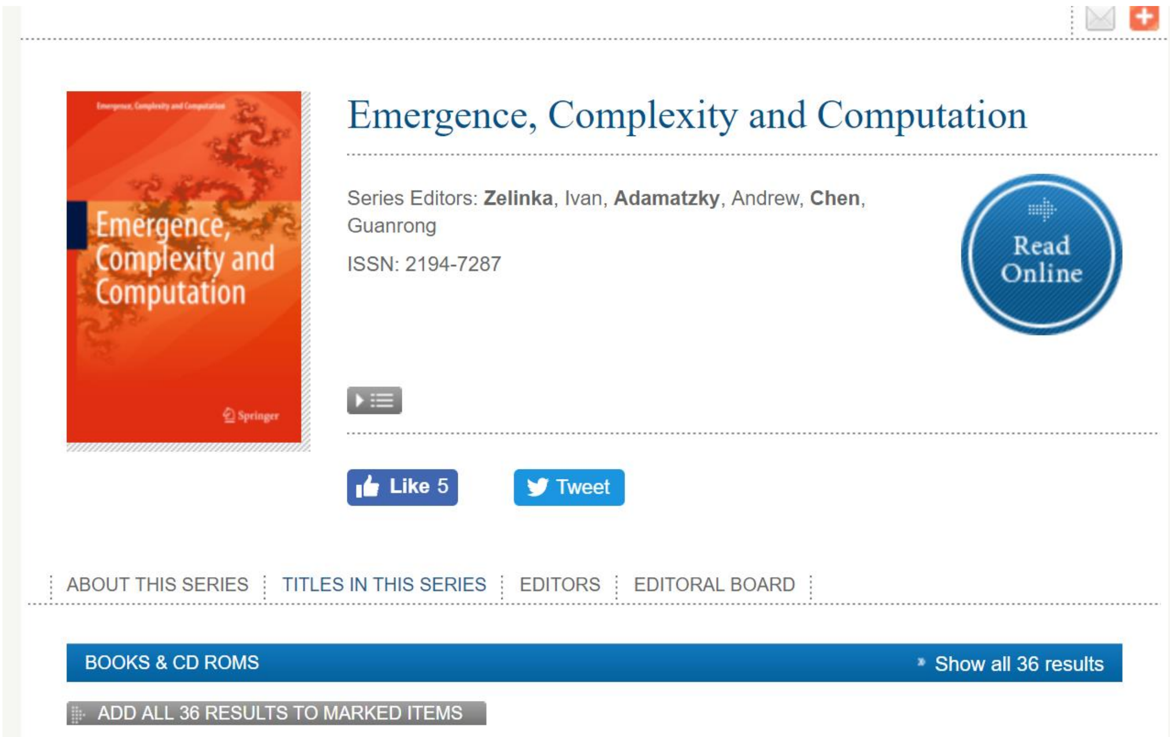
Kojecky, L., Zelinka, I., Prasad, A., Vantuch, T. and Tomaszek, L., 2018. Investigation on unconventional synthesis of astroinformatic data classifier powered by irregular dynamics. *IEEE Intelligent Systems*, *33*(4), pp.63-77.

BIA Perspectives in Astrophysics

- Model parameter estimation
- Model synthesis
- ANN synthesis and learning
- Prediction
- Anomaly detection
- Object identification
- Design and tune another algorithms used in astrophysics

Call for Chapters

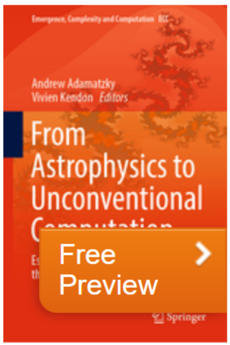
- ivanzelinka.eu



Call for Chapters

- ivanzelinka.eu

Emergence, Complexity and Computation



From Astrophysics to Unconventional Computation

Essays Presented to Susan Stepney on the Occasion of her 60th Birthday

Editors: **Adamatzky**, Andrew, **Kendon**, Viv (Eds.)

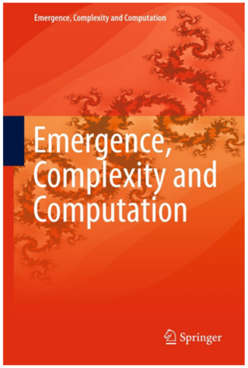
Is a tribute to Susan Stepney's ideas and achievements in the areas of computer science, complex systems, formal programming, unconventional computing, artificial chemistry and cybernetics

» see more benefits

Call for Chapters

Springer springer.com

- ivanzelinka.eu
- Book editors:
  - Ivan Zelinka
  - …
  - …



Call for Book Chapters In Intelligent Astrophysics

Published in the book series

Emergence, Complexity and Computation

Series Editors: I. Zelinka, A. Adamatzky, G. Chen

The Intelligent Astrophysics publishes new developments, advancements and selected topics in the fields of artificial intelligence and related algorithms in astrophysical data processing. The book focuses on all aspects of reality-based computation approaches from an interdisciplinary point of view in all important areas of astrophysics as the signal processing in the radio astronomy, image processing with machine learning, deep learning applications on various astrophysical tasks, evolutionary computation in classification and modelling of astrophysical events, archive processing and anomaly detection in live streams from robotic telescopes and more. It presents new ideas and interdisciplinary insight on the mutual intersection of subareas of artificial intelligence and computation and its impact and limits to any astrophysical problems.

Preliminary deadlines:
Chapter submission: 30th November 2019
Notification of acceptance and reviews: 31st January 2020
Camera ready submission: 29th February 2020
Book production: Spring 2020

THANK YOU FOR YOUR ATTENTION

ivan.zelinka@ieee.org

www.ivanzelinka.eu

Copyright