# lecture 11 - Evolutionary Algorithms bit.ly/atBIC Syntactic Operations akerna Development X n<sub>p</sub> **X**<sub>1</sub>

biologically-inspired computing

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#### course outlook

key events coming up



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### final project schedule

#### Projects

bit.lv/atBIC

Due by May 7<sup>th</sup> in Brightspace, "Final Project 483/583" assignment

ALIFE 2025

- Not necessarily to submit to actual conference due date
  - May 4 full paper, July 4, abstract
- https://2025.alife.org/
- Max 8 pages, author guidelines:
- https://2025.alife.org/calls#paper-call
- MS Word and Latex/Overleaf templates
- Preliminary ideas by March 7
  - Submit to "Project Idea" assignment in Brightspace.
- Individual or group
  - With very definite tasks assigned per member of group

# **ALIFE 2025**

Tackle a real problem using bio-inspired algorithms, such as those used in the labs.



Reusing and expanding labs is highly encouraged.

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# readings

until now
<ul> <li>Class Book         <ul> <li>Floreano, D. and C. Mattiussi [2008]. Bio-Inspired Artificial Intelligence: Theories, Methods, and Technologies. MIT Press. Preface, Chapters 1 and 4.</li> </ul> </li> <li>Lecture notes         <ul> <li>Chapter 1: What is Life?</li> <li>Chapter 2: The logical Mechanisms of Life</li> <li>Chapter 3: Formalizing and Modeling the World</li> <li>Chapter 4: Self-Organization and Emergent Complex Behavior</li> <li>Chapter 5: Reality is Stranger than Fiction</li> <li>Chapter 6: Von Neumann and Natural Selection             <ul> <li>posted online @ http://informatics.indiana.edu/rocha/i-bic</li> </ul> </li> <li>Papers and other materials         <ul> <li>Optional</li> <li>Nunes de Castro, Leandro [2006]. Fundamentals of Natural Computing: Basic Concepts, Algorithms, and Applications. Chapman &amp; Hall.</li> <li>Chapter 2, 7, 8</li> <li>Chapter 3, sections 3.1 to 3.5</li> </ul> </li> </ul></li></ul>
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# Von Neumann's generalization of Turing's tape

as a general principle (system) of evolution or open-ended complexity













# importance of the "external tape"

### in biology

- The "information turn"
  - Unlike Schrödinger, Turing and Von Neumann had no direct effect on molecular biology
  - But the "external tape" separated from the constructor (semiotic closure) has become an unavoidable principle of organization of biocomplexity
  - A new synthesis?

 In 1971 Brenner: "in the next twenty-five years we are going to have to teach biologists another language still, [...] where a science like physics works in terms of laws, or a science like molecular biology, to now, is stated in terms of mechanisms, maybe now what one has to begin to think of is algorithms. Recipes. Procedures."

"The concept of the gene as a symbolic representation of the organism — a *code script* — is a fundamental feature of the living world and must form the kernel of biological theory. [...] at the core of everything are the tapes containing the descriptions to build these special Turing machines." (Sydney Brenner)

Brenner, Sydney. [2012]. "Life's code script." Nature 482 (7386): 461-461.





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# Turing's tape

# fundamental principle of organisms as cybernetic mechanisms







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### information not just biochemistry

# decoupled information



Millar & Lambert [2013]. "Ancient DNA: Towards a millionyear-old genome." Nature. doi:10.1038/nature12263

Orlando, L. et al. [2013] Nature doi.org/10.1038/nature12323



What other components of life can be fossilized and recovered with biochemical reproducibility this way?



Schweitzer et al [2007] Science. 316 (5822): 277-280 Schweitzer et al [2009] Science. 324 (5927): 626-631. Schroeter et al [2017] J. Proteome Res. 16 (2):920–932 Lee et al [2017] Nature Communications 8: 1422. Service, R. [2017] Science. DOI: 10.1126/science.aal0679

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from autonomy to "semiopoiesis"

the tape is not necessarily self-contained in cells, brains, or machines

decoupling and externalization enable collective behavior



two roles of information data/program (Turing) passive/active (Von Neumann) description/construction-function (Pattee) genotype/phenotype (Biology)

"Let the whole outside world consist of a long paper tape". —John von Neumann, 1948

Rocha, L.M. [2000] *Annals N.Y. Acad. Sci.* **901**(1): 207-223. Rocha, L.M. & W. Hordijk [2005] *Artificial Life* **11**:189 - 214.



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from autonomy to "semiopoiesis"

the tape is not necessarily self-contained in cells, brains, or machines



# (material) symbols in the wild

# stigmergy



decoupling and externalization enable collective behavior

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# (material) symbols in the wild

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#### endogenous retroviruses

# Turing machines written on other Turing machines (naturally)



Sequences from RNA and DNA viruses found in host genomes Retroviral genomes, account **for 6 to 14% of host genomes** ~8% of human DNA. endogenous retroviruses (ERVs) comprise more DNA than host proteome.

Weiss & Stoye [2013]. "Our Viral Inheritance." Science.340 (6134): 820-821.



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### endogenous retroviruses

# Turing machines written on other Turing machines (naturally)



### The social symbiome

semiotic control networks enable new, interacting levels of organization and selection, which take control of genes, organisms, and even societies.



Mercer et al. [2012] Targeted RNA sequencing reveals the deep complexity of the human transcriptome. *Nat. Biotech.* **30**, 99–104.

**Examples**: eukaryotic RNA/DNA complexity, vertebrate immunity, eusociality, cultural constraints on reproduction, GMOs (including via CRISPR), viral pandemics, etc.

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### The social symbiome

semiotic control networks enable new, interacting levels of organization and selection, which take control of genes, organisms, and even societies.



Eukaryote **complexity in regulation**: regulatory components larger than coding, genome size is secondary: 10-100K times more energy per gene than bacteria (# proteins expressed) Lane & Martin [2010] *Nature* **467**(7318):929–934.

**Examples**: eukaryotic RNA/DNA complexity, vertebrate immunity, eusociality, cultural constraints on reproduction, GMOs (including via CRISPR), viral pandemics, etc.

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### The social symbiome



# Turing's tape

# fundamental principle of organisms as cybernetic mechanisms







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# Turing's tape



from cybernetic mechanisms to bio-inspired algorithms

#### History of evolutionary computation OBUCTORY ANALYSIS WITH **Evolutionary Operation** IDLOGY, CONTROL AND ARTIFICIAL INTELLIG • Box (1957) Perturbations to continuous variables followed by selection to improve industrial productivity **Evolution Strategies** Rechenberg (1960's), Schweffel (1970's) • To optimize real-valued parameters in wind-tunnel experiments Real-valued genotypes under variation and selection Evolutionary Programming • Fogel, Owens, and Walsh (1966) JOHN H. HOLLAND Evolution of tables of state-transition functions (diagrams) under mutation and selection Artificial ecosystems Genotype RNA Conrad and Pattee (1970) DNA Population of artificial cells evolving with genotype and phenotype translation (code) Other early evolution-inspired algorithms and models amino acid Barricelli CA-like model(1957), game-strategy model (1963) chains Symbiogenetic evolution development • Friedman (1957, 1959), Bledsoe (1961), Bremmermann (1962) phenotype **Genetic Algorithms** environmenta ramifications • John Holland (1960's and 1970's) Adaptation in Natural and Artificial Systems, University of Michigan Press, 1975. (MIT Press, second edition 1992) BINGHAMTON rocha@indiana.edu casci.binghamton.edu/academics/i-bic UNIVERSITY

# modeling genetic-based (open-ended) evolution

### optimization

### via genetic algorithms

- Search algorithms based on the mechanics of Natural Selection
  - Holland, Conrad, Fogel
  - Based on distinction between a machine and a description of a machine
    - Solution alternatives for optimization problems

Direct analysis depends on Knowing the function Existence of derivatives continuity



"hill-climbing"

"hop" on the function and move along the steepest direction until a local extrema is found

Random Search directionless

Enumerative Search Search point by point



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# fitness landscapes

# examples



### genetic algorithms



Variation mechanisms to search new points

### computational evolution

### artificial genotype/phenotype mapping



### coding

# in genetic algorithms

# Solution space encoded as finite-length string over a finite alphabet

- E.g. {0, 1}
- GA's exploit coding similarities
  - Searches the code space, not the solution space



# genetic algorithms

# The workings



### probabilistic selection

# biased population generation

- Solution space encoded as finite-length string over a finite alphabet
  - E.g. {0, 1}
- GA's exploit coding similarities
  - Searches the code space, not the solution space
- Searches the space with many alternatives in parallel
  - Avoids getting trapped in local optima
  - Higher probability of finding better solutions
- Not random search
  - Search towards regions with likely improvement
  - Better solutions reproduce more often
    - Does not work in very rugged, chaotic, uncorrelated landscapes



### reproduction

## Modeling fitness selection





### Variation: crossover

# 1) Reproduction: New population is generated

- a) Selection
  - Select two parent chromosomes from a population according to their fitness
- b) Variation: Crossover
  - With a *crossover probability* produce offspring pair by recombining parents.



### reproduction

# Variation: mutation





# genetic algorithms



### computational evolution

### artificial genotype/phenotype mapping



#### evolving computer programs

- Fogel, Owens and Walsh (1966)
   Artificial Intelligence through simulated evolution. Wiley.
   Evolution of finite-state machines
- John Koza (1992) at Stanford University
  - Genetic Programming: On the programming of computers by means of Natural Selection. MIT Press.







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# tree encodings

- Evolving computer programs to perform a task
  - No strict genotype-phenotype mapping
  - LISP programs
    - Can be expressed in the form of parse trees



# the workings



5) Go back to 3)





R\*[(PI\*C)  $-\sqrt{R}$ ]

### PI/{[(PI/PI)/(PI/PI)]}





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#### crossover Choose random point in each parent's tree Exchange subtrees beneath to produce offspring Allows size of program to increase or decrease **R+(√PI\*D)** PI/{[(PI/PI)/(PI/PI)]} R PI R PI PI PI PT R+{\/PI\*[(PI/PI)/(PI/PI)]} PI D PI PI/D PI PI PI PI **BINGHAMTON** rocha@indiana.edu UNIVERSITY OF NEW YORK casci.binghamton.edu/academics/i-bic

# mutation

- Choose random point in a tree
- Replace subtree beneath with random tree





# crossover demo



# Mutation demo



Architecture-altering operations





1) Generate Random population of trees/programs

- 2) Evaluate Fitness Function for each program
  - Desired I/O, simplicity, speed
- 3) Reproduce next generation
  - Selection by fitness
  - Variation
    - crossover and mutation
  - Fill new population
- 4) Go back to 2) until stop criteria is met
  - Desired fitness
  - Specified number of generations
  - Convergence

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# applications

- Optimal control
- Planning
- Symbolic regression
  - Fit real data
    - Example: Uncover laws of physics
      - Schmidt M., Lipson H. (2009) "Distilling Free-Form Natural Laws from Experimental Data," Science, 324 (5923): 81 85.
    - Binary Classification
  - Software Tool
    - Eureqa: https://www.creativemachineslab.com/eureqa.html
- Robot strategies
  - Robocup
- Evolvable hardware







### Eureqa

### A symbolic regression tool

# Eureqa: https://www.creativemachineslab.com/eureqa.html



### Eureqa

A symbolic regression tool

# Eureqa: https://www.creativemachineslab.com/eureqa.html



# Types of encoding

- Binary encodings
  - Typically fixed-length
- Many-letter encoding
  - Larger alphabet (e.g. graph-generation grammars)
- Real-valued encodings
  - Genes take real values
- Tree Encodings
  - Genetic programming
- Indirect Encodings
  - Modeling Phenotype <u>development</u> or post-transcription processes
    - L-Systems, Dynamical systems, evolutionary robotics



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### Cellular automata

homogenous lattice of state-determined systems



#### Cellular automata

encoding in GA with binary encoding



### Evolving CA rules

#### With genetic algorithms



Das,R., Mitchell,M., Crutchfield,J.P., [1994]. "A genetic algorithm discovers particle-based computation in cellular automata". In: *Parallel Problem Solving from Nature - PPSN III*. Davidor,Y., Schwefel,H.-P., Manner,R. (Eds.), Springer-Verlag, pp. 344-353.

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# evolutionary algorithms

# to evolve photos with numerical encodings





Original

128 circles

256 circles



In silico means that its simulated or implemented in silicon (ie silicon transistors in a computer)





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### real and integer encoding

# In genetic algorithms



- 1) Crossover is performed in the same way
- 2) Mutation assigns a random number in a given interval
- 2) More computationally demanding for Reals
- 3) Attention to crossover points
  - 1) Conversion to binary avoids crossover issues, but longer genotypes



# neuroevolution

### Evolutionary algorithms to optimize neural networks

- Capabilities (not in gradient-based ANN)
  - Generation of ANN building blocks
    - Activation functions
    - Hyperparameter optimization
    - Architecture and learning algorithm search and optimization
- Massive Paralellism
  - Population of solutions

# nature machine intelligence

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Review Article Published: 07 January 2019

# Designing neural networks through neuroevolution

<u>Kenneth O. Stanley</u> <sup>[]</sup>, <u>Jeff Clune</u> <sup>[]</sup>, <u>Joel Lehman</u> <sup>[]</sup> & <u>Risto Miikkulainen</u> <sup>[]</sup>

Nature Machine Intelligence 1, 24–35 (2019) Cite this article

Stanley, K.O., Clune, J., Lehman, J. et al (2019). Designing neural networks through neuroevolution. *Nat Mach Intell*, 24–35.



Example HyperNEAT network, view from front (left) and back (right)

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### evolving morphologies and robots with indirect encodings

Karl Sim's simulations, Genobots, and the Golem project



# Next lectures

<ul> <li>Class Book</li> <li>Floreano, D. and C. Mattiussi [2008]. <i>Bio-Inspired Artificial Intelligence: Theo</i> <i>Methods, and Technologies</i>. MIT Press.</li> <li>Chapter 7</li> <li>Lecture notes <ul> <li>Chapter 1: What is Life?</li> <li>Chapter 2: The logical Mechanisms of Life</li> <li>Chapter 3: Formalizing and Modeling the World</li> <li>Chapter 4: Self-Organization and Emergent Complex Behavior</li> <li>Chapter 5: Reality is Stranger than Fiction</li> <li>Chapter 6: Von Neumann and Natural Selection</li> <li>posted online @ casci.binghamton.edu/academics/i-bic</li> </ul> </li> </ul>	ries,
<ul> <li>Optional         <ul> <li>Nunes de Castro, Leandro [2006]. Fundamentals of Natural Computing: Basic Concep and Applications. Chapman &amp; Hall.</li> </ul> </li> </ul>	ots, Algorithms,

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