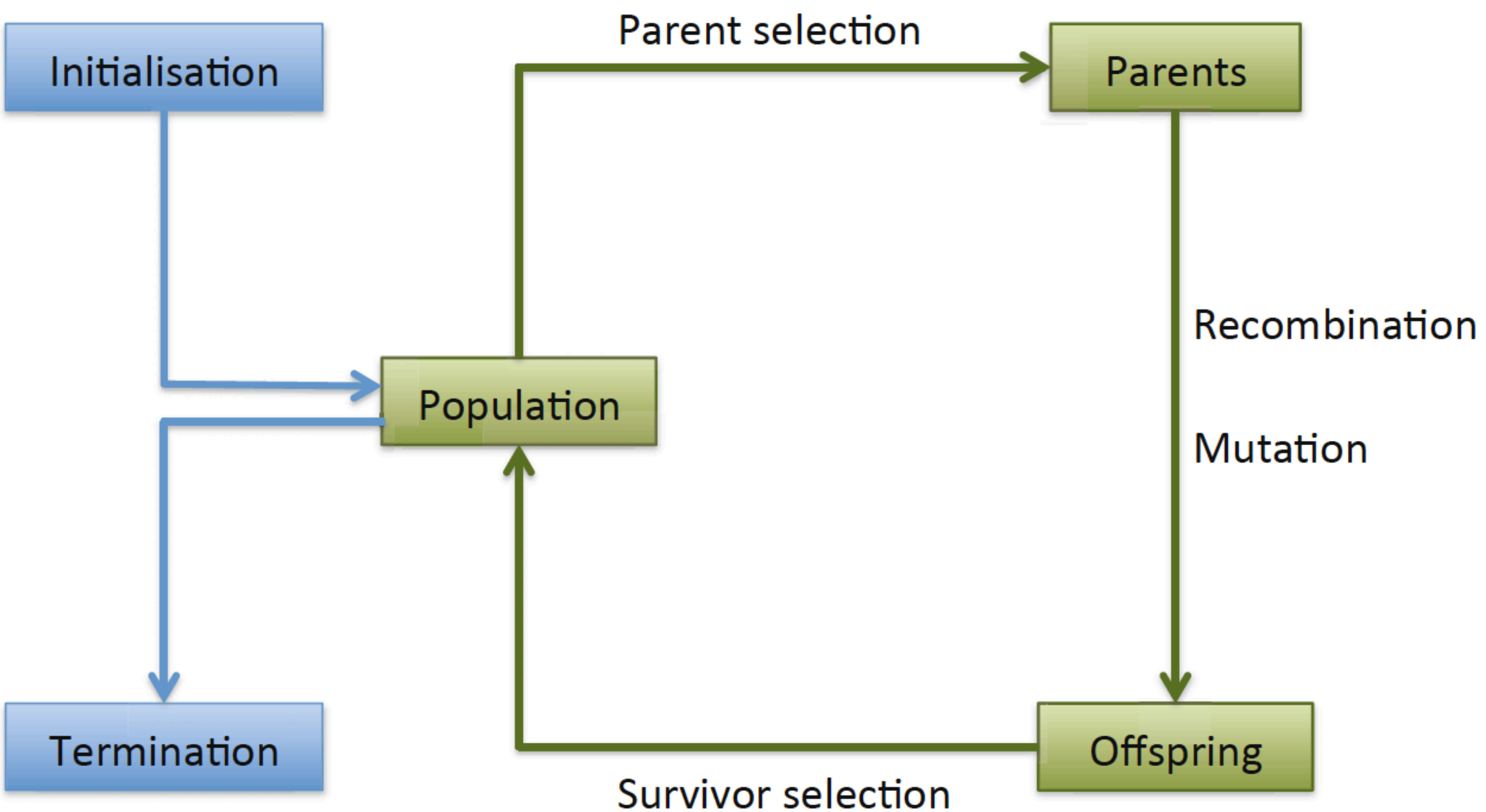
26: Last Lecture

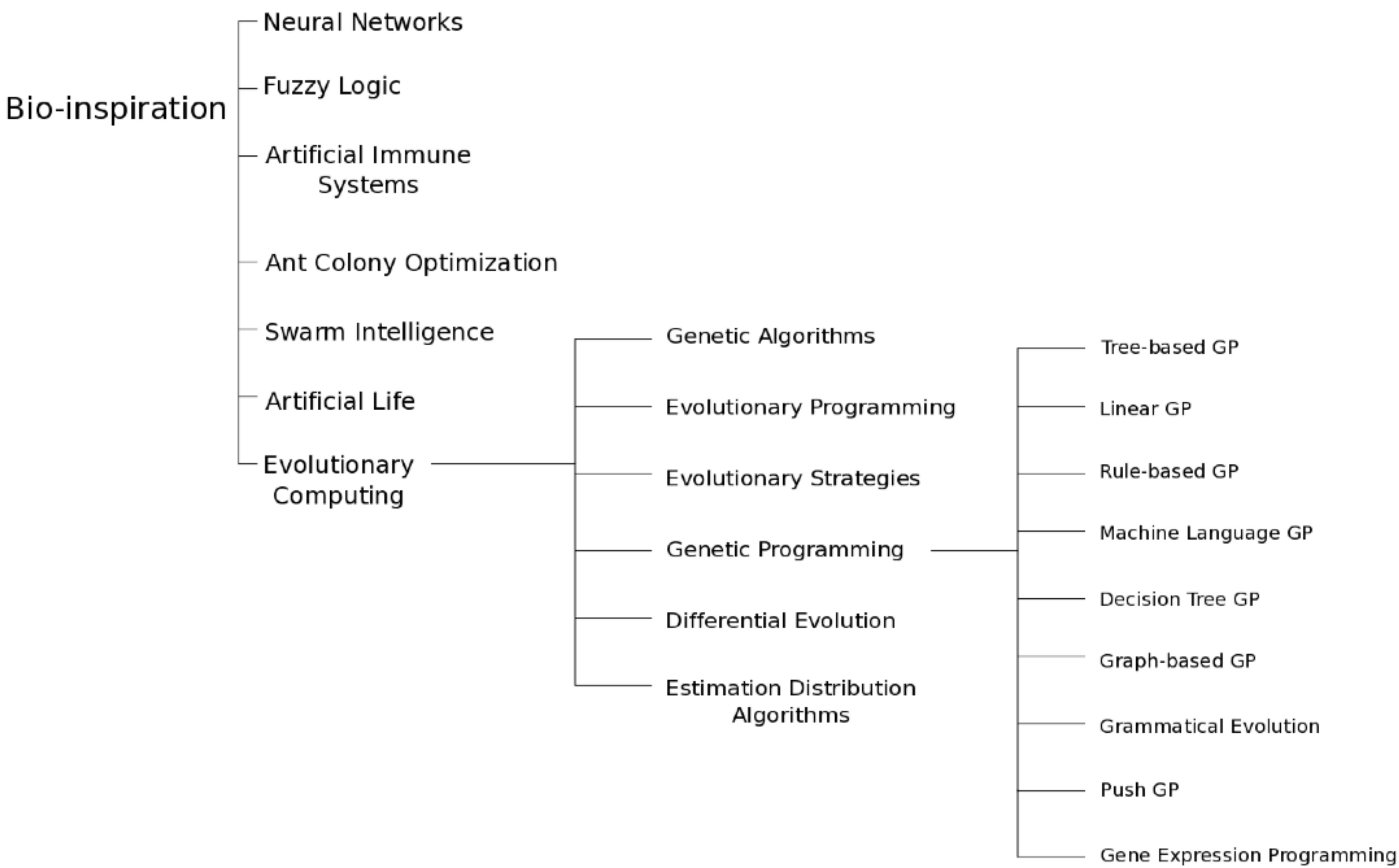
- Evolutionary algorithms summarized
- Advanced techniques
- Common troubleshooting
- Applications of EAs

Prof. Ting Hu, School of Computing, Queen's University

General scheme of EAs



Bio-inspired computing



Work flow of designing an EA

- Understand the problem
- Representation (definition of individuals)
- Evaluation function (or fitness function)
- Population
- Parent selection mechanism
- Variation operators, recombination and mutation
- Survivor selection mechanism (replacement)

Advanced techniques

- Optimizing parameters
  - parameter tuning
  - parameter control on the fly
- Preserving diversity
  - fitness sharing, crowding, speciation
  - multi-population island
  - spatial EAs
  - novelty search and quality-diversity (illumination)
- Multi-objective evolution
- Co-evolution
- Memetic algorithmes

Algorithm performance metrics

- One-off problems vs. online problems
- Average number of evaluations to a solution (AES)
- Mean best fitness at termination (MBF)
- Success rate of runs funding a solution with acceptable quality (SR)
- Statistical comparison and significance

Trouble shooting

- Ineffective search or search space too large
- Mutation and/or crossover too disruptive
- Premature convergence
- Fitness progression too slow

Trouble shooting

- Ineffective search or search space too large
  - need better presentation of candidate solutions
- Mutation and/or crossover too disruptive
  - need better customized variation operators
- Premature convergence
  - need better population management (i.e., selections)
  - parameter optimization
  - preserve diversity
- Fitness progression too slow
  - hybridization, domain knowledge

New frontiers of evolution research and applications

- Evolution as meta-learning

nature COMMUNICATIONS

ARTICLE

Check for updates

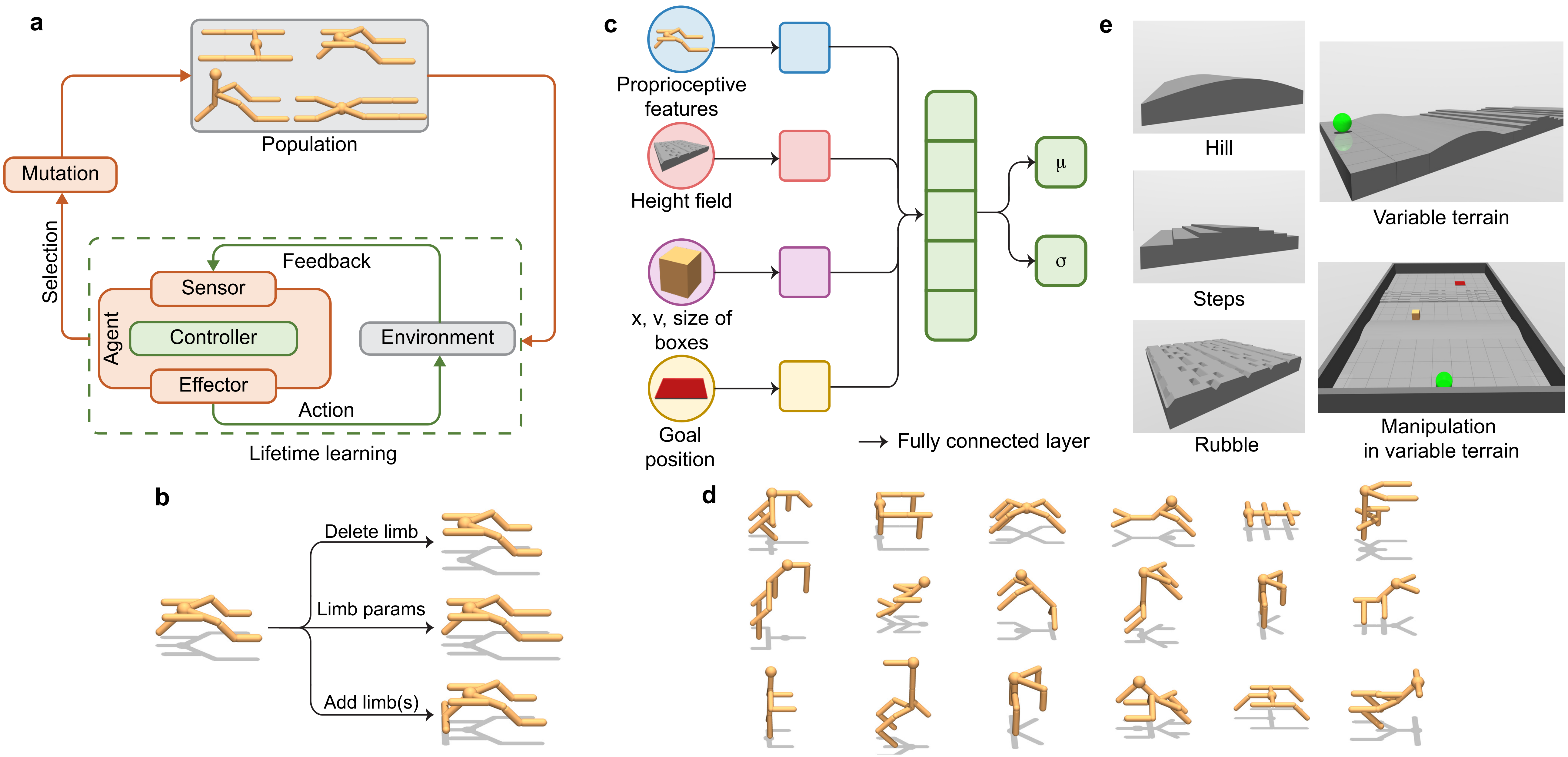
https://doi.org/10.1038/s41467-021-25874-z OPEN

Embodied intelligence via learning and evolution

Agrim Gupta [1✉], Silvio Savarese[1], Surya Ganguli[2,3,4] & Li Fei-Fei [1,4✉]

New frontiers of evolution research and applications

- Evolution as meta-learning



New frontiers of evolution research and applications

- Evolution as meta-learning

REVIEW ARTICLE
https://doi.org/10.1038/s42256-018-0006-z

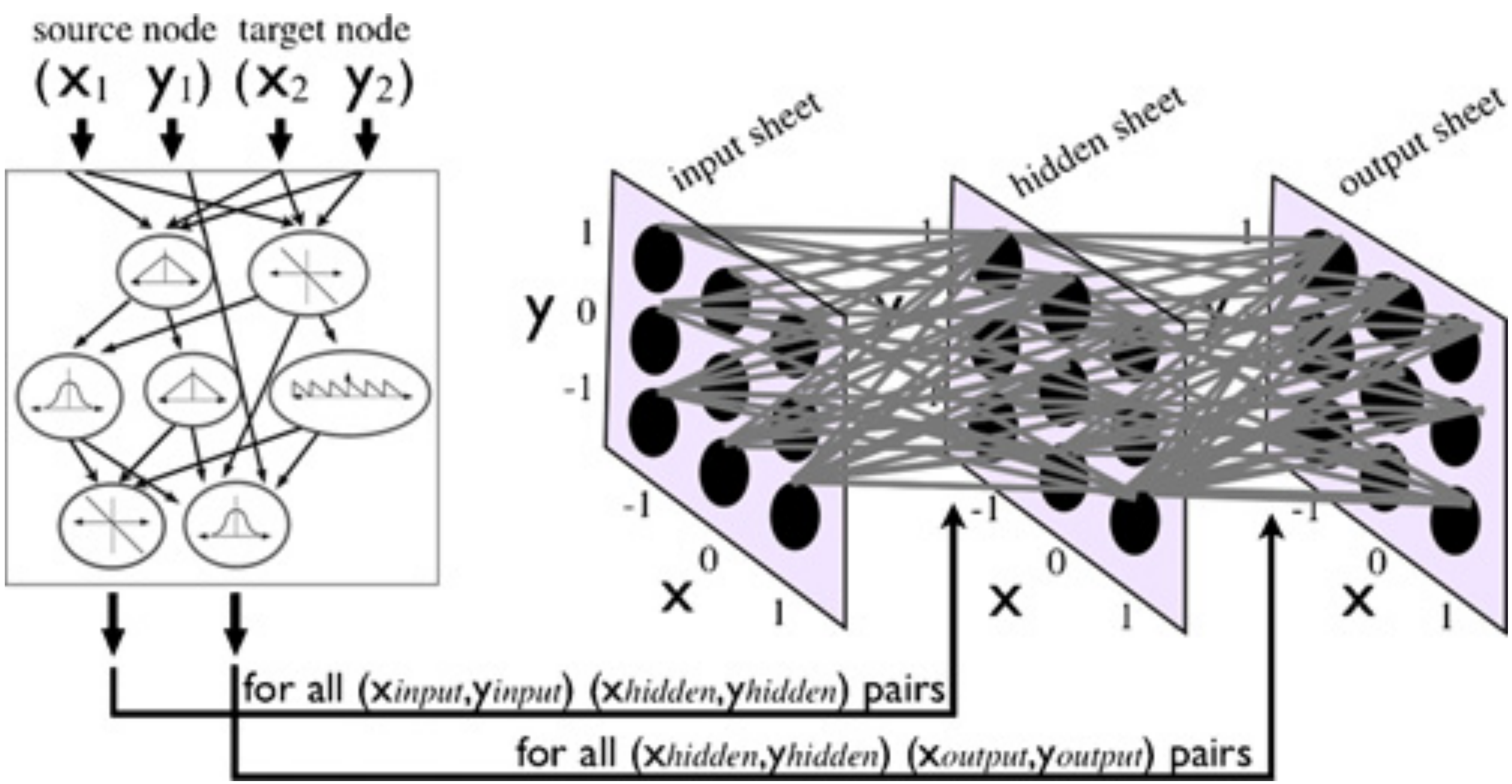
nature machine intelligence

Designing neural networks through neuroevolution

Kenneth O. Stanley[1,2*], Jeff Clune[1,3*], Joel Lehman[1*] and Risto Miikkulainen[4,5*]

New frontiers of evolution research and applications

- Evolution as meta-learning



New frontiers of evolution research and applications

- Evolution for creative AI

SN Computer Science (2021) 2:163
https://doi.org/10.1007/s42979-021-00540-9

ORIGINAL RESEARCH

Creative AI Through Evolutionary Computation: Principles and Examples

Risto Miikkulainen[1]

Received: 1 August 2020 / Accepted: 22 February 2021 / Published online: 23 March 2021
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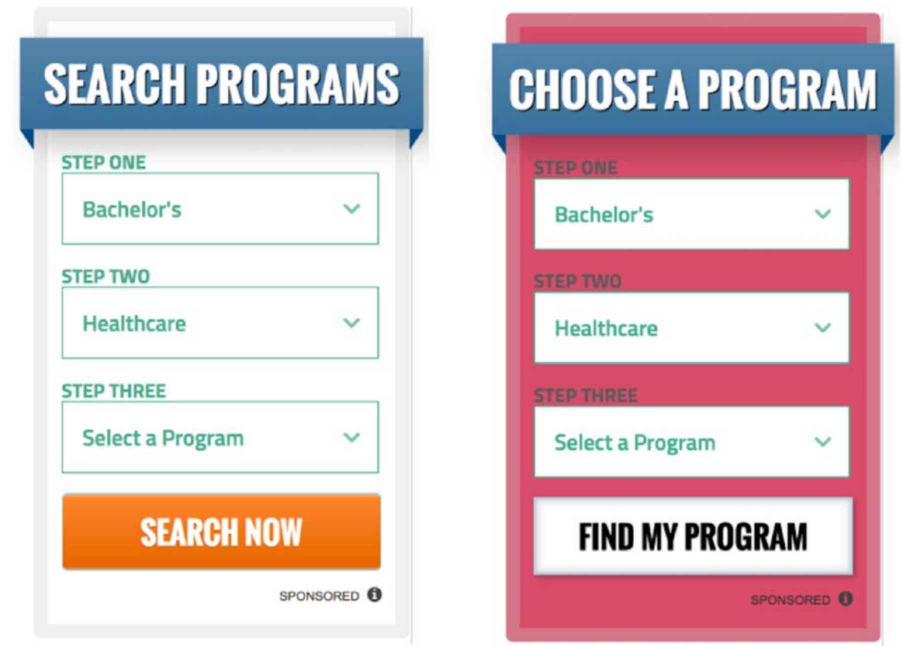
Abstract
The main power of artificial intelligence is not in modeling what we already know, but in creating solutions that are new. Such solutions exist in extremely large, high-dimensional, and complex search spaces. Population-based search techniques, i.e. variants of evolutionary computation, are well suited to finding them. These techniques make it possible to find creative solutions to practical problems in the real world, making creative AI through evolutionary computation the likely "next deep learning."

New frontiers of evolution research and applications

- Evolution for creative AI



(a) Control (b) Evolved

New frontiers of evolution research and applications

- Evolution for explainable AI

The intersection of Evolutionary Computation and Explainable AI

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EC and XAI

- XAI within EC
  - Landscape analysis
  - Hyper-heuristics and parameter selection
- EC for XAI
  - generate glass-box models such as decision trees and rules
  - fairness
  - generate counterfactual explanations

Thank you!

Let me know what you think!