Open-ended Neuroevolution

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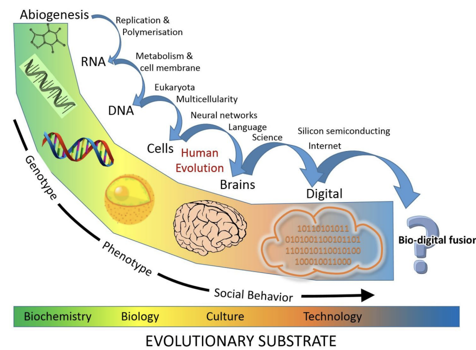
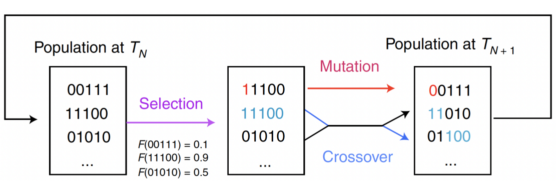
Open-ended Discovery of Complex Behavior

- Neuroevolution can find successful behavior for given tasks.
- Biologicy is open-ended: Operates continuously, without specific goals.
- Elements of open-endedness could lead more powerful neuroevolution:
  1. Neutrality with weak selection
  2. Enhanced exploration through extinction events
  3. Evolvable representations
  4. Expressive (not just indirect) encodings.
  5. Major transitions in complexity
  6. Co-evolution of body and brain
  7. Co-evolution of brain and static environments.
  8. Co-evolution of brain and dynamic environments.



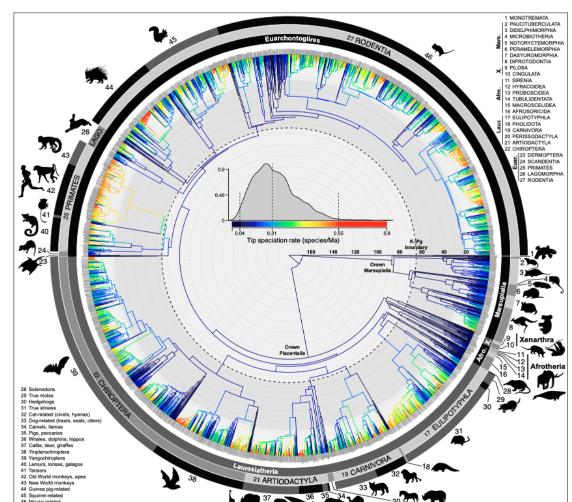
1. Standard approach to computational evolution

- Evolutionary computation often uses strong selection for fast optimization.
- Small populations and engineered operations lead to quick convergence.
- This approach works for well-defined problems but may miss solutions.
- Engineers are highly impatient!



Biological Approach

- Biological evolution involves large populations and weak selection.
- Many mutations are neutral and do not affect fitness.
- Diversity stays in the population even when not immediately beneficial.
- Biology has a lot of patience :-)



Opportunity with Increased Computational Power

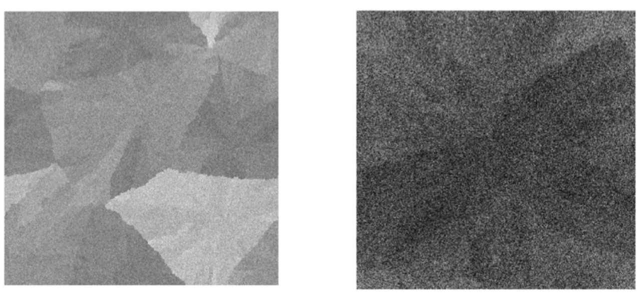
- Impatience because of limited computational power.
- With billionfold increases, new approaches are possible.
  - Large populations, neutral mutations, deep time, large simulations.
  - Develop foundation models for neuroevolution?
- Computational scaleup led to deep learning and GenAI; similar advances possible for neuroevolution as well.

2. Extinction Events in Biological Evolution

- Five large-scale extinction events have altered the course of evolution.
- Example: The Cretaceous-Paleogene event displaced dinosaurs with mammals.
- Question: Are extinction events accidents or do they serve a role in evolution?
- Extinctions may reset evolution, favoring higher evolvability and complexity.

Computational Experiments on Extinctions

- Extinction events can be studied in an abstract setting:
  - Individuals encoded with a 2D location/niche and evolvability.
  - Evolvability determines how likely the offspring is to occupy another niche through mutation.
- Starting from the center, population evolves until all niches are filled.
- Further evolution only through drift; evolvability stagnates.

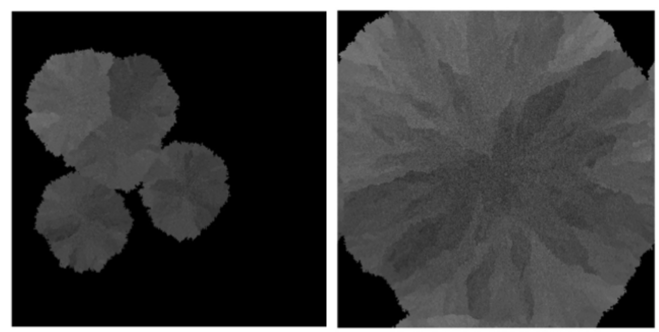


(a) Control - 2,000 Gens. (b) Control - 15,000 Gens.

Lighter=more evolvable

Evolvability Through Extinctions

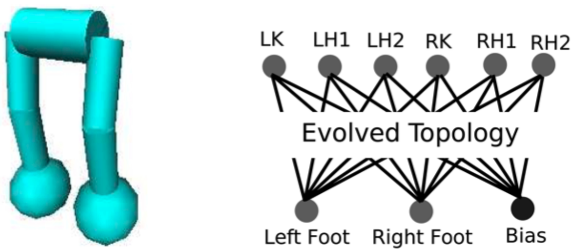
- Extinction events remove most of the population, leaving a few individuals.
- The ones with higher evolvability fill more niches.
- Repeated extinction thus favors individuals with higher evolvability.
- Extinction events accelerate evolution!



Soon after extinction Later after extinction

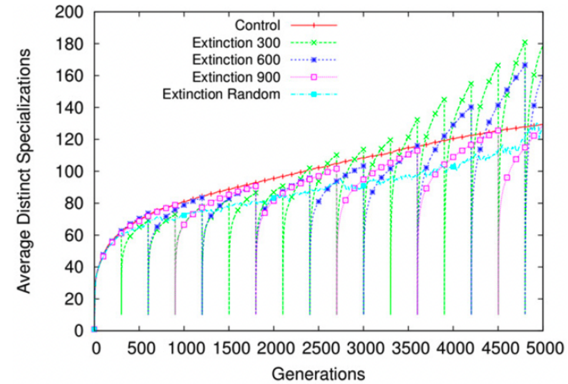
Extinction in the Bipedal Walker Domain

- Extinction events can affect behavioral evolution as well.
- E.g. Bipedal walker:
- Input: Whether each foot touches the ground.
- Output: motors on left and right knee and hip.
- Nice: Where does it end up?



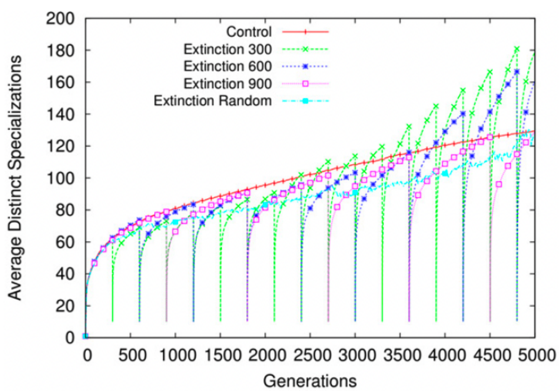
Extinction in the Bipedal Walker Domain

- Extinction events lead to faster rebounds.
- After each extinction, the population fills more niches than before.
- Extinction accelerates evolution and increases novelty in solutions.



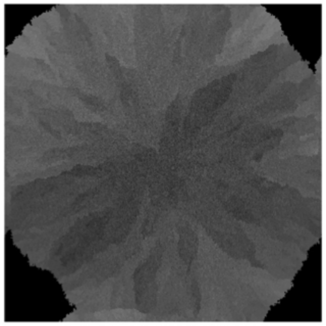
Conclusion on Extinction Events

- Extinction events have the potential to reset evolution and favor more evolvable solutions.
- Even at smaller scales, extinction events may be beneficial for long-term innovation.
- Combining extinction events with large populations and weak selection could accelerate openended evolution in neuroevolution systems.



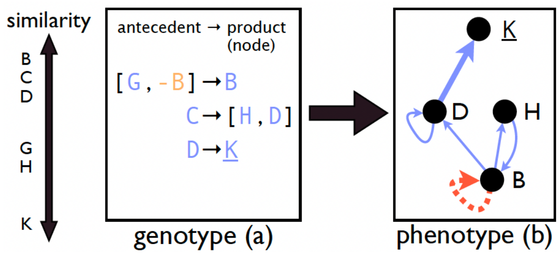
3. Evolvable Representations

- Evolutionary algorithms often focus on creating and maintaining diversity in genotypic and phenotypic space (quantity)
- Evolvability makes it possible to create larger changes faster (quality).
  - The main idea is to adapt the genotype-phenotype mapping.
  - Indirect encodings are crucial to supporting evolvability.
- Both of these approaches can lead to better high-fitness solutions.



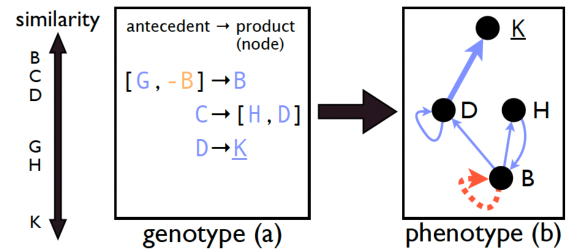
GRNs Can Support Evolvability

- Genetic Regulatory Networks (GRNs) are indirect encodings that evolve over time.
- GRNs encode rules for building neural networks.
- Products in the GRN create nodes and connections between them.
- Evolvability emerges through continuous mutations in the rules.



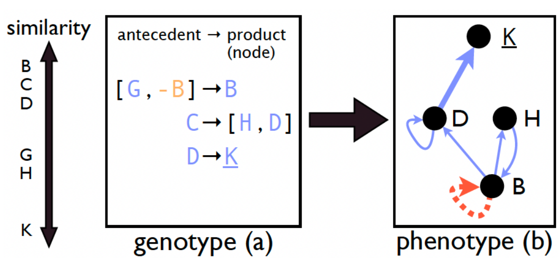
Constructing neural networks from GRNs

- Each rule has a regulatory(antecedent) and transcription(product) region.
- Variables are regulatory factors (proteins) with tolerance (similarity)
- When existing products match antecedents within tolerance;
  1. Products are generated as nodes.
  2. Antecedent nodes are connected to product nodes.



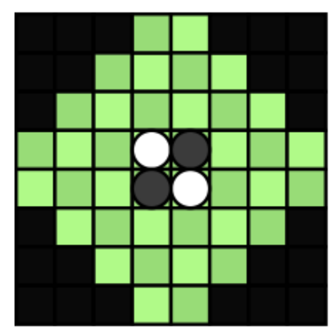
GRN $\rightarrow$ Neural Net Example

- Starting with G and no B, B is created (as a node)
  - With input from G (not shown).
  - With an inhibitory link B→B.
- B is close to C: H and D are created (as nodes)
  - With connections from B.
  - H is close to G: connection from H to B.
  - D is close to C: connection from D to itself.
  - D is close to C: connection from D to H (not shown).
- D creates K, the output node
  - With a connection from D.



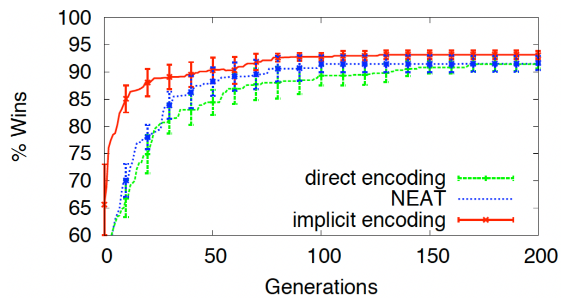
Test Domain: Nothello

- GRN-based neuroevolution was tested in Nothello (simplified Othello):
  - Still: Take turns to place pieces (black/white)
  - Still: Sandwiched pieces are flipped.
  - But: Smaller diamond-shaped board.
  - But: Player with the fewest pieces wins.
- Simpler, faster, but still challenging.



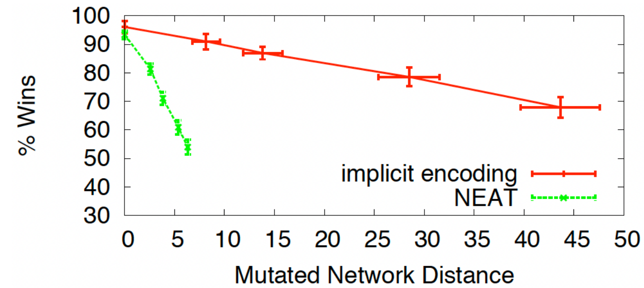
Performance in the Nothello Domain

- Neural networks evolved as heuristic evaluators.
- Coevolution process: Each network evaluated against others in the population.
- The GRN-based indirect encoding evolved better strategies faster than evolution of feature weights and NEAT.



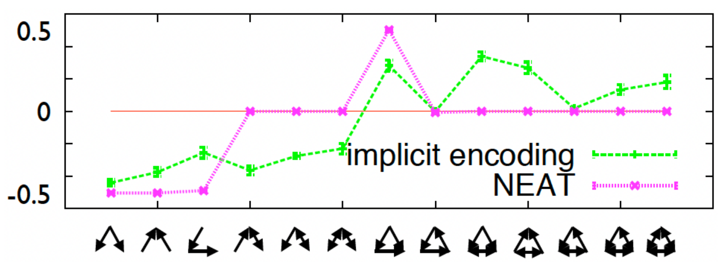
Performance Arising from Evolvability

- In coevolution, the fitness function changes continuously.
- High evolvability is thus a major advantage in coevolution.
- Evolvability is measured as the average fitness of mutated offspring.
- The GRN-based encoding results in more robust mutations compared to NEAT.



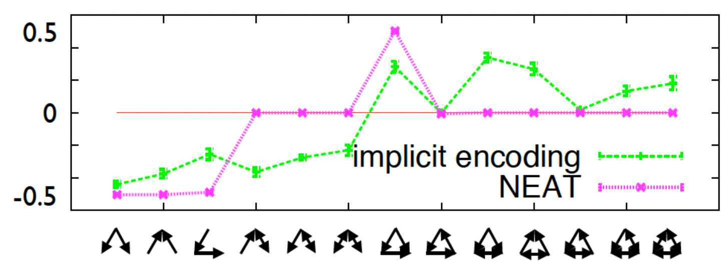
Network Motifs with High Evolvability

- The GRN-based approach discovers a wider variety of network motifs.
- Recurrent motifs are common in GRN networks, supporting robust evolvability.
- This leads to more complex behaviors and open-ended discovery.



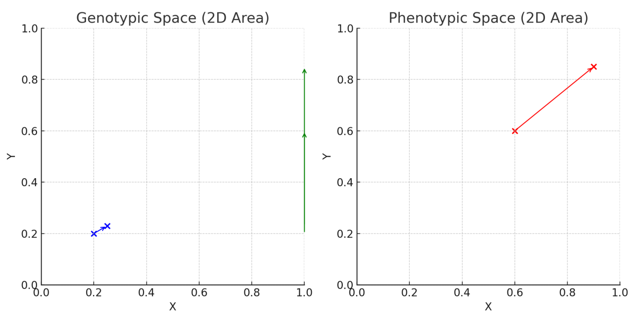
Conclusion on Evolvable Representations

- Evolvable representations support long-term evolution and adaptation to changing environments.
- Indirect encodings like GRNs enable evolvability through soft, continuous mutations.
- Evolvability is especially useful in coevolution where the fitness function changes continuously.
- Evolvability is thus essential for open-ended discovery of increasingly complex solutions.



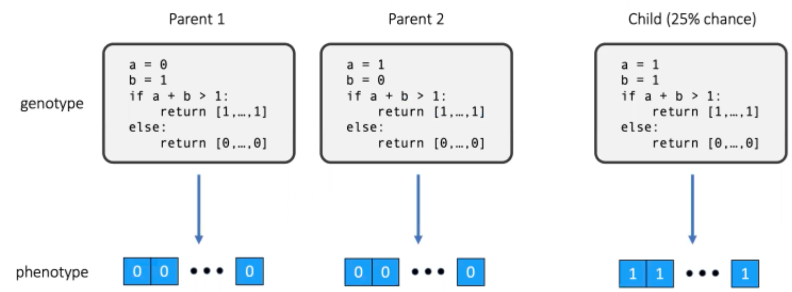
4. Expressive Encodings Overview

- Expressive encodings allow for large jumps in the search space.
- In particular, small changes in the genotype can result in large changes in the phenotype (miracle jumps).
- Standard evolutionary algorithms with direct encodings cannot easily make such jumps.
- Expressive encodings are highly evolvable and open-ended.



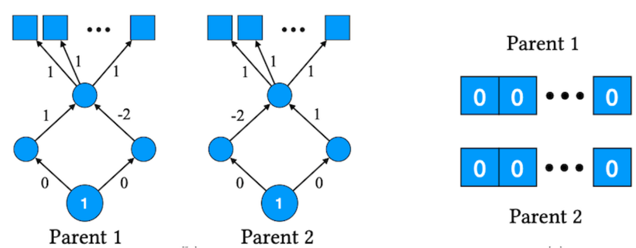
Example of Miracle Jumps: GP

- Genetic programming (GP) can create miracle jumps through conditionals or specific segments.
- E.g. two GP parent phenotypes are all-0s.
- But there's a 25% chance that their crossover is all-1s.



Example of Miracle Jumps: NE

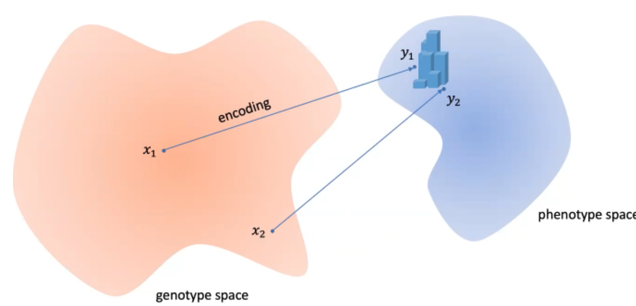
- Neuroevolution (NE) can also produce miracle jumps.
- E.g. neural networks evolved to produce a bit string.
- The two parents differ only in the weights of the second layer.
- With uniform crossover, 25% chance of jumping from all-0s to all-1s.
- Direct encoding cannot achieve such jumps as effectively.



(Zero bias and sigmoid activation function: 0→0.5)

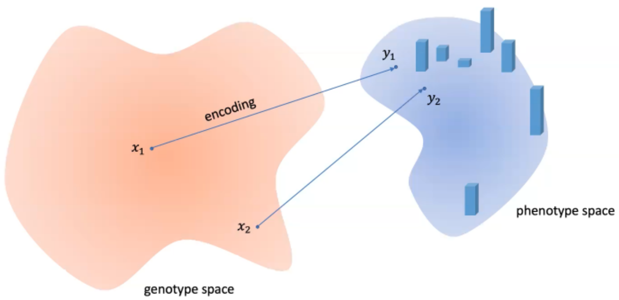
Power of Expressive Encodings

- In a standard crossover, offspring phenotype is somewhere in between the parent phenotypes.



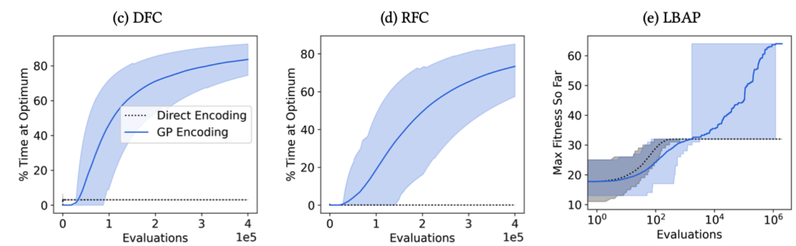
Power of Expressive Encodings

- With Expressive Encodings, the offspring phenotypes can be anywhere in the space.
- Even with a simple crossover, recombination samples from an arbitrary distribution of child phenotypes.



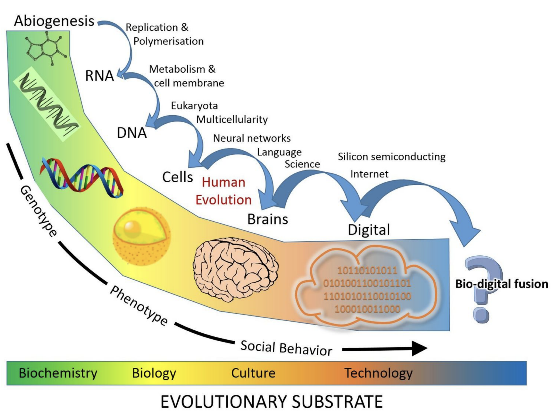
Power of Expressive Encodings

- Expressive encodings outperform direct encodings theoretically and experimentally (Deterministic Flipping, Random Flipping, Large Block Assembly).
  - Even with flat landscape, break through eventually.
- Much of the genetic structure is shared, similar to biological systems.
- A good idea to use GP or NN as a representation; best chance for open-ended evolution!



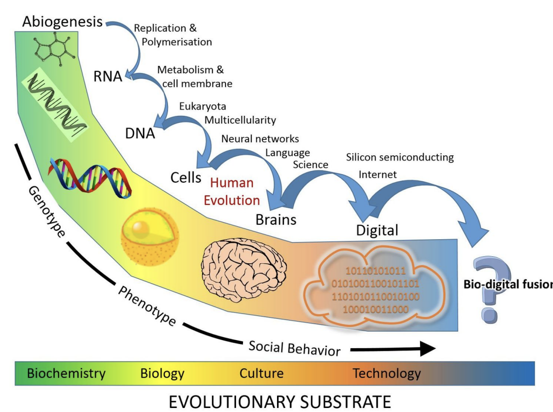
5. Major Transitions

- Open-ended discovery may require major transitions in complexity.
- Biological evolution progressed through several transitions, e.g.:
  - From self-replicating molecules to chromosomes.
  - From single cells to multicellular organisms.
  - Formation of eusocial societies and language.
- Each transition results in more complex individuals and cooperative roles.



Challenges in Establishing Major Transitions

- Not fully understood in biology.
- Key questions:
  - How do individuals specialize and lose the ability to reproduce independently?
  - Are there multiple levels of selection or just one?
- Computational studies can help, but simulating major transitions in behavior is challenging.



Mechanisms for Major Transitions

- Ingredients for major transitions exist in computational experiments:
  - Evolving cooperative structures (e.g., Hierarchical ESP).
  - Agents communicating and coordinating to achieve shared goals.

  Also (to be discussed next):
  - Coevolution of body and brain.
  - Emergence of new challenges through competitive processes (environment, adversaries).
- However, actual transitions have not been discovered in computation yet.