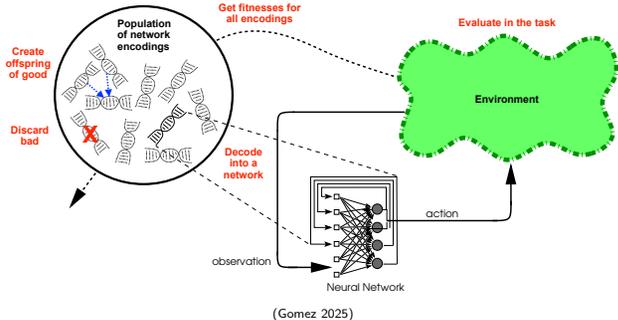


Direct vs Indirect Encodings in Neuroevolution

- ▶ Direct encodings map genotype directly to phenotype (one-to-one).
- ▶ Indirect encodings compress genotype.
- ▶ A simple genotype can then be mapped into a complex phenotype.



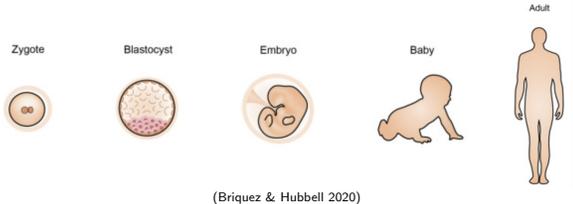
Indirect Encodings

Risto Miikkulainen

February 21, 2026

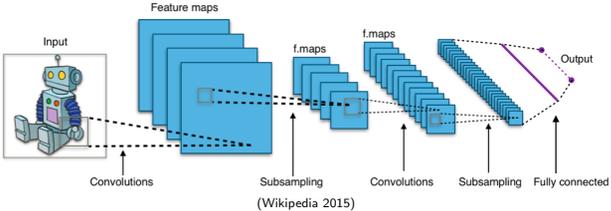
Why Indirect Encodings?

- ▶ Biological organisms develop from a single starting point.
- ▶ Morphogenesis leads to the creation of complex structures.
- ▶ Reuse of structural motifs creates regularity.
- ▶ Structures specialize based on context.



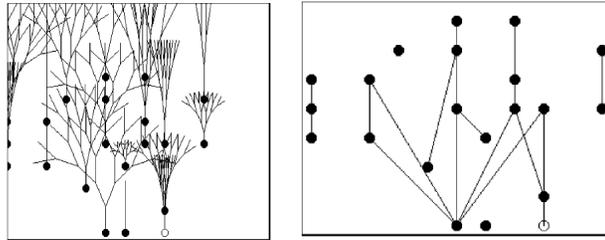
The Role of Regularities in Encoding

- ▶ Regularity enables compression and compactness of neural networks.
- ▶ E.g. convolutional neural networks reuse feature detectors across multiple locations.
- ▶ Neuroevolution could discover similar patterns without human intervention.



Applying Reaction-Diffusion to Neural Networks

- ▶ Diffusion models axonal growth, and chemical reactions model interactions between axons and cells.
- ▶ Neuron definitions include location of cell bodies and axon branching rules.
- ▶ Growth is pruned to remove non-useful connections, allowing for indirect encoding.

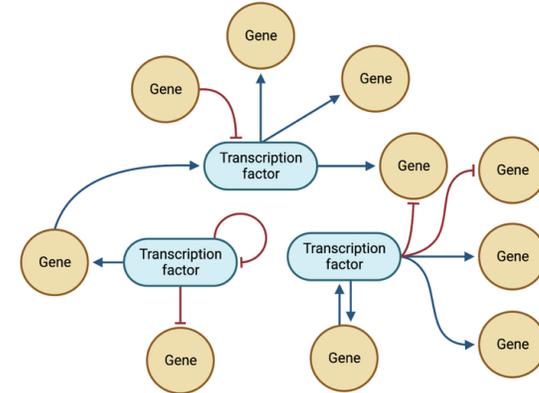


(Nolfi & Parisi 1991)



Genetic Regulatory Networks (GRNs)

- ▶ Gene expression creates proteins.
- ▶ Gene expression is followed by complex networks of gene interactions .
 - ▶ Promoting and inhibiting expression
 - ▶ Mediated by transcription factors (proteins).
- ▶ Much of the complexity in the phenotype is due to GRNs.

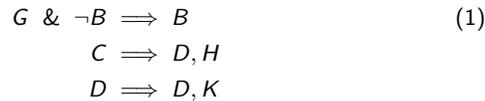


(BioRender 2025)

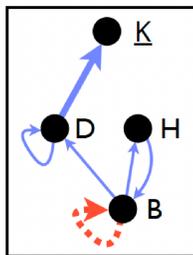


Applying GRNs to Neural Networks

- ▶ Indirect encoding through GRNs can evolve complex neural structures.
- ▶ Proteins represent neurons; connections form when the proteins match.
- ▶ For example,



- ▶ If protein G is present and B is absent, then B is produced.
- ▶ B is similar to C, so D and H are produced.
- ▶ H is similar to G, which enhances B until there's enough B.

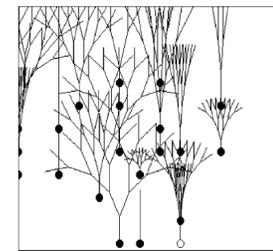


(Reisinger & Miikkulainen 2007)

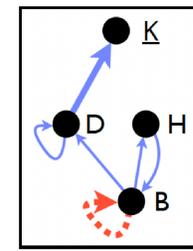


Challenges and Potential of Cell-Chemistry Approaches

- ▶ Cell-chemistry approaches are powerful but complex to implement.
- ▶ GRNs and reaction-diffusion models offer rich representations but are difficult to scale.
- ▶ Simplifications such as Boolean GRNs or string-based genomes help balance complexity and effectiveness.
- ▶ Complexity of GRNs may lead to open-ended evolution.



(Nolfi & Parisi 1991)



(Reisinger & Miikkulainen 2007)



Grammatical Encodings

- ▶ Biological organisms exhibit repetition with variation.
- ▶ Examples: Vertebral columns, fingers, bilateral symmetry.
- ▶ Grammatical encodings aim to capture such structure.
- ▶ They are a high-level abstractions of development.



(HealthCentral 2024)



(Freepik 2024)

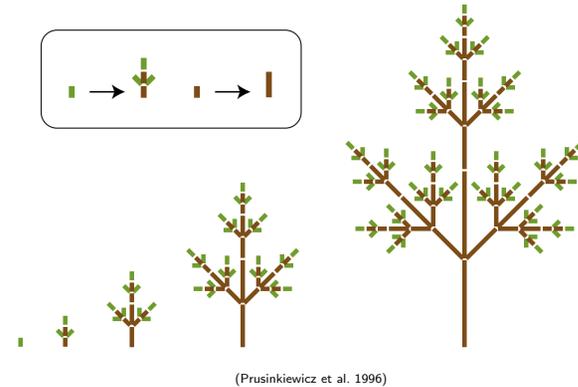


(Dreamstime 2024)



Lindenmayer Systems (L-systems)

- ▶ L-Systems (Lindenmayer systems) represent a formal grammar-based method.
- ▶ Each rewrite rule step represents a stage in development.



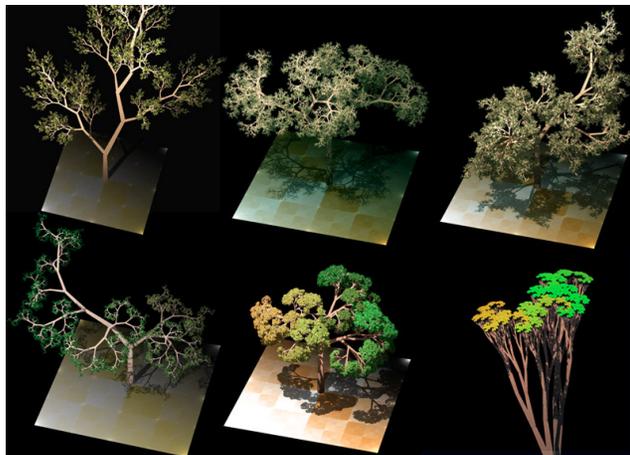
(Prusinkiewicz et al. 1996)

L-System rewriting steps to generate plant-like structures.



L-Systems in Practice

- ▶ L-Systems can produce realistic plant structures and virtual foliage.
- ▶ Used in visual effects for movies like Iron Man 3 and Avatar.
- ▶ Iterative rewriting generates increasingly complex structures.

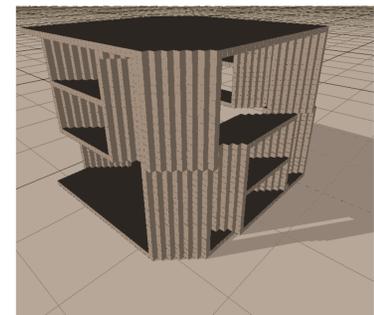
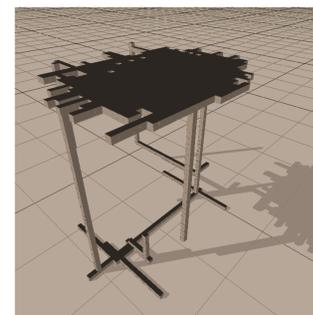


(Wikipedia 2024)



Evolving Designs with L-Systems

- ▶ L-Systems can be optimized using evolutionary search methods.
- ▶ E.g. evolving table designs
 - ▶ Direct encoding lacks reuse of components, producing more irregular structures.
 - ▶ Indirect encoding produces more symmetrical, modular, and regular structures.
 - ▶ More natural and aesthetically pleasing.

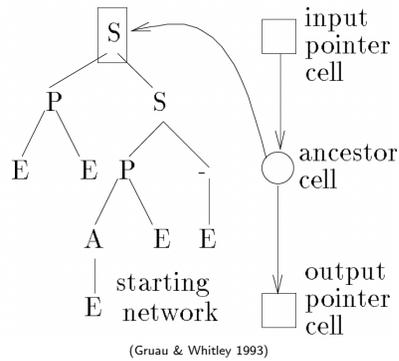


(Hornby & Pollack 2001)



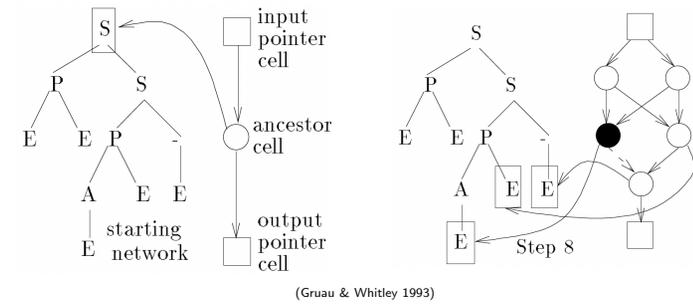
Grammatical Encoding of Neural Networks

- ▶ Cellular encoding (CE) uses grammars to describe neural network construction step by step.
- ▶ A grammar tree encodes instructions for network modifications.
- ▶ Each node of the grammar tree specifies a network transformation.



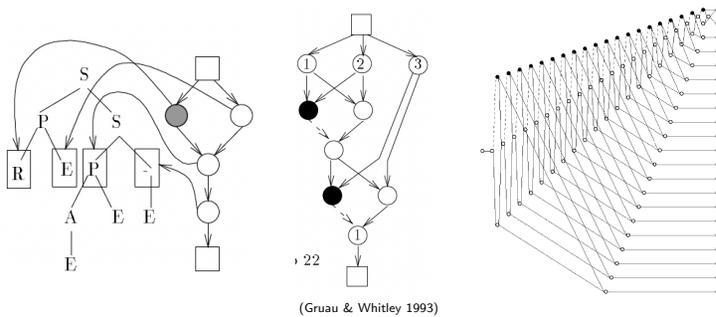
Cellular Encoding Example: XOR Network

- ▶ An example of CE: XOR neural network construction.
- ▶ Sequential and parallel divisions of the ancestor node.
- ▶ Final network implements XOR logic after several steps.



Recurrency in Cellular Encoding

- ▶ Recurrency allows repeating entire structures in a grammar.
- ▶ By traversing the grammar multiple times, larger networks can be evolved.
- ▶ E.g. parity and symmetric networks can be created with recurrency.



Learning as Indirect Encoding

- ▶ Biological development also involves learning from interaction with the environment.
- ▶ Learning mechanisms allow individuals to adapt their structure and behavior during their lifetime.
- ▶ Synergy between evolution and learning can be a powerful computational mechanism.

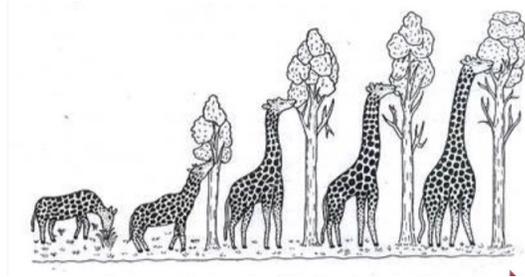


(DALL-E 2024)



Lamarckian Evolution

- ▶ Lamarckian evolution suggests that acquired traits can be inherited.
- ▶ Discredited in biology: Darwinian selection achieves the same result.



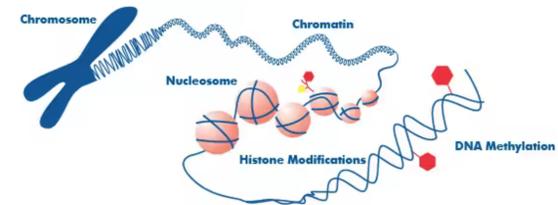
(Chegg 2024)

Inheritance of acquired characteristic: A stretched neck.



Epigenetic Evolution

- ▶ However, epigenetic mechanisms have recently been found with a similar effect.
- ▶ Parts of DNA covered in methylation during lifetime.
- ▶ The methylation can be inherited.
- ▶ Methylation affects RNA transcription, and eventually behavior.
- ▶ E.g. fearfulness that lasts for two or more generations.

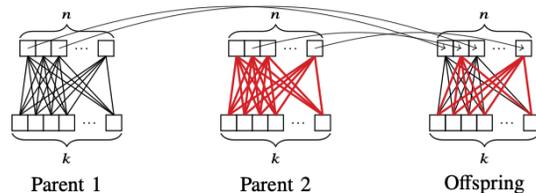


(Novus Biologicals 2024)



Computational Lamarckian Evolution

- ▶ Computationally easy to take advantage of Lamarckian and epigenetic principles.
- ▶ Can be applied e.g. to evolving deep learning networks.
- ▶ Gradient-based learning is combined with evolutionary exploration of architectures.
- ▶ Success e.g. in evolving convolutional architectures for image processing.



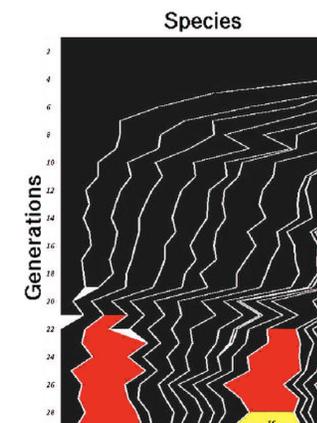
(Hadjivanov & Blair 2021)

Crossover of convolutional networks.



Challenges in Lamarckian Evolution

- ▶ Gradient-based learning can lead to a loss of diversity.
- ▶ Population diversity can be maintained using ensembling, data batching, speciation.
- ▶ Balancing exploration and learning is an ongoing research challenge.

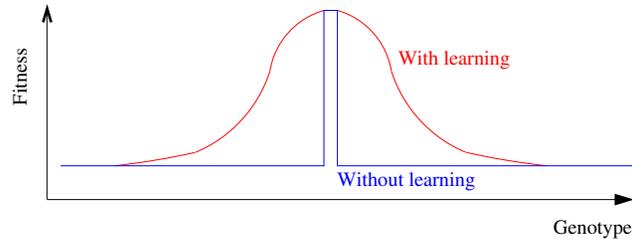


(Stanley & Miikkulainen 2002)



Darwinian Alternative: The Baldwin Effect

- ▶ The Baldwin effect suggests that learning guides evolution without encoding changes in the genome.
- ▶ Learning helps evolution discover promising individuals by broadening the search space.
- ▶ Even just random walk helps solve difficult problems, such as the needle-in-the-haystack.
 - ▶ Probability of success depends on initial distance to the goal.

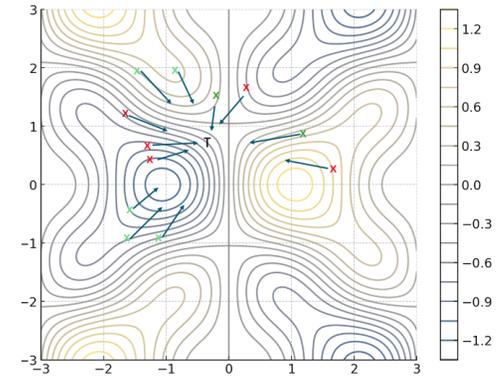


(Hinton & Nowlan 1987)



Synergetic Development

- ▶ Surprise: Evolution discovers good starting points for learning rather than near-optimal solutions.
 - ▶ Learning will happen, so evolution discovers how to take it into account.
 - ▶ A synergy between learning and evolution.
- ▶ Solutions are more robust and more effective.



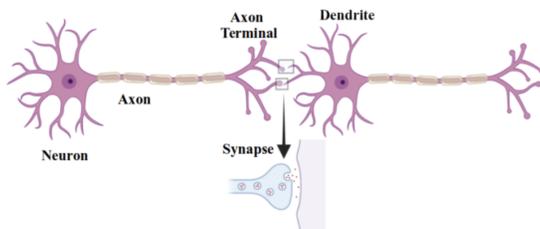
(Risi et al. 2025)



Hebbian Learning as an Online Adaptation Mechanism

- ▶ Hebbian learning is a local learning mechanism where neurons that fire together wire together.
- ▶ It requires no learning targets and is more biologically plausible than gradient descent.
- ▶ Hebbian learning can drive adaptive behavior by strengthening useful connections.
- ▶ Not powerful enough to learn complex behavior, but could adapt to changing environments.

$$\Delta w_{ij} = \alpha_i o_i o_j - \beta_{ij} w_{ij} \quad (2)$$



(Das et al. 2022)



Hebbian Adaptation

- ▶ Hebbian learning can evolve networks capable of switching tasks based on experience.
- ▶ For example, turning on a light and then moving to a target area.
- ▶ It provides flexibility, but does it outperform recurrent activation for adaptation?



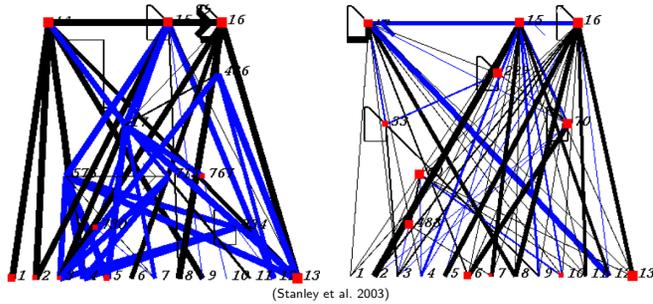
(Floreano & Urzelai 2000)

Adapting to the switch location.



Hebbian Learning vs. Recurrent State

- ▶ In simple tasks, recurrent networks can adapt by representing a state (e.g. light on or off).
- ▶ Recurrent networks without Hebbian learning are simpler and often more efficient.
- ▶ However, weight adaptation persists over many trials, and may be an advantage in more complex tasks.



Network with Hebbian learning vs. network with simple recurrence.



Development Conclusions

- ▶ Development can be utilized to construct complex neural networks.
 - ▶ Based on low-level chemistry, high-level grammars, and learning processes.
 - ▶ Indirect encoding of solutions.
- ▶ Understanding biology; building artificial systems.
- ▶ The interplay between evolution, development, learning, and adaptation remains an intriguing research direction.



(DALL-E 2024)

