Investigating Evolvability in a Genetic Regulatory Network Model

Mathematics and Computer Science Department Seminar

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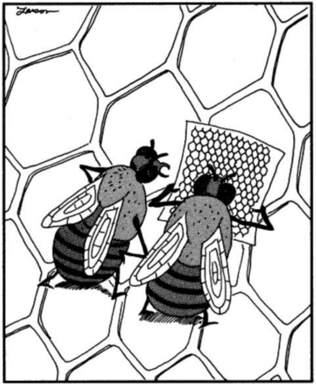
Evolutionary Algorithm

Search



"Face it, Fred—you're lost!"

- common scenario: you can recognize a good solution, but you don't know how to find one
- encountered by computer scientists (and everyone else, too)
- common approach: try different options, evaluate outcomes to help choose next options to try
- this is called search

Evolutionary Algorithm: Vocabulary

- individual
- population
- fitness
- genotype
- phenotype
- mutation

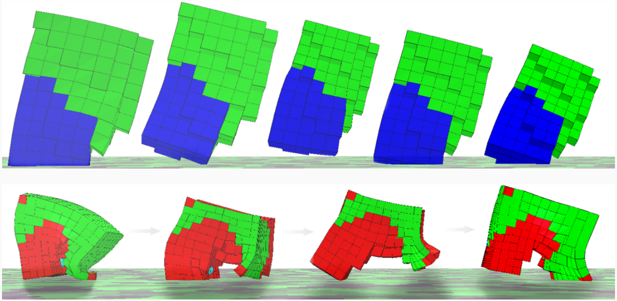


Figure 1: Illustrative examples of candidate solutions in an evolutionary algorithm [Cheney et al., 2013, Figures 1, 12].

Evolutionary Algorithm: Overview

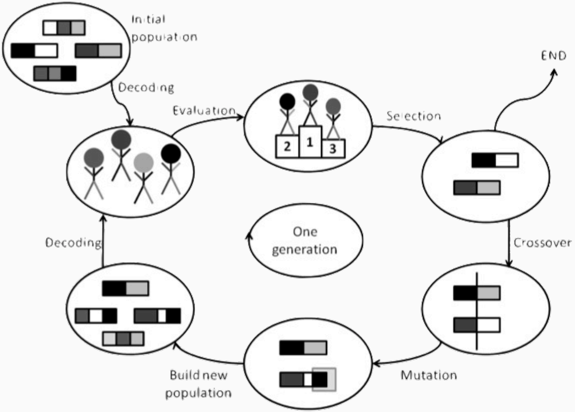


Figure 2: A schematic illustration of the evolutionary algorithm [Prothmann et al., 2009, Figure 1].

Evolutionary Algorithm: Example

Figure 3: Evolution in Action [Cheney et al., 2013]

Evolutionary Algorithm: Problem Statement

What makes an evolutionary algorithm work?

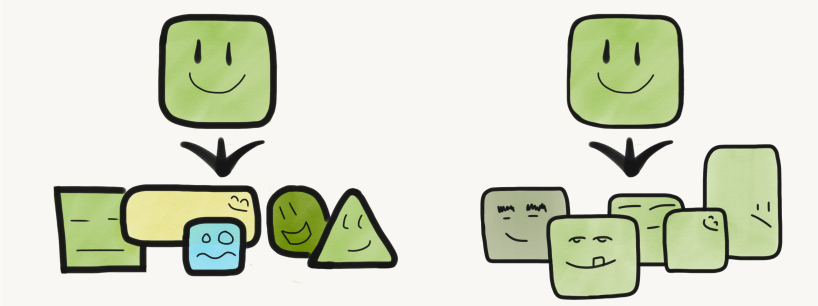
Defining Evolvability

Defining Evolvability

consensus: the amount of useful variation generated by the evolutionary process

- evolvability as the amount of **novel variation** generated
- evolvability the proportion of variation that is **useful**

Evolvability as Novel Variation



(a) high individual evolvability (b) low individual evolvability

Figure 4: An illustration of individual evolvability, considering evolvability as heritable variation [Wilder and Stanley, 2015].

Evolvability as Bias towards Useful Variation

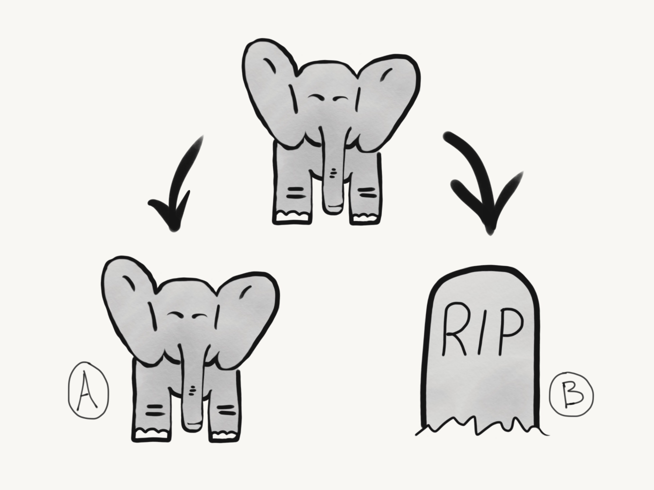


Figure 5: Illustration of robustness; high evolvability left and low evolvability right [Downing, 2015].

Evolvability as Bias towards Useful Variation

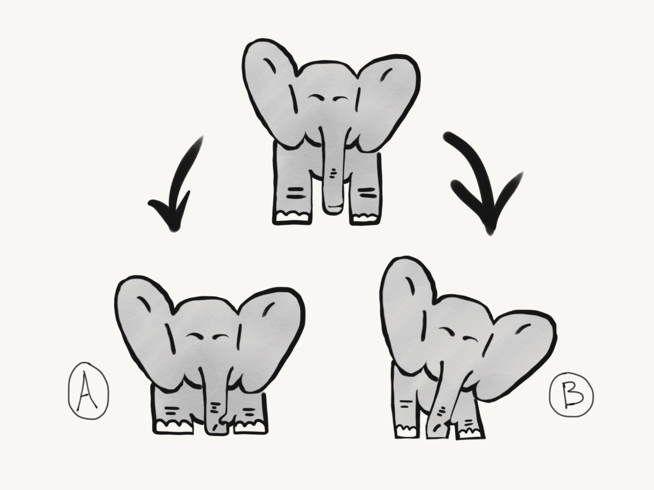


Figure 6: Illustration of developmental constraint; high evolvability left and low evolvability right [Smith et al., 1985, Tuinstra et al., 1990].

Generating and Reading an Evolvability Signature

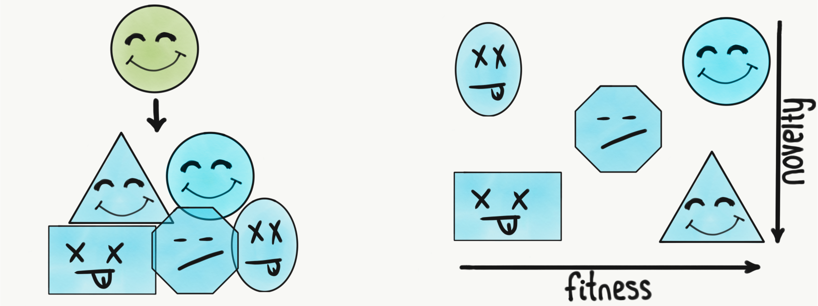


Figure 7: Cartoon illustration describing the creation and layout of an evolvability signature diagram [Tarapore and Mouret, 2015].

Causes of Evolvability: Intuition

Summary

big idea: internal system configuration determines the outcomes of change to the system

Computer Science Intuition: Spaghetti Code

idea: software without compartmentalization, error handling, with hard-coded constants, etc. is much more difficult to alter in useful ways

(a) spaghetti code

(b) regular code

Figure 8: A cartoon comparison of spaghetti and regular code.

Computer Science Intuition: Spaghetti Code

idea: software without compartmentalization, error handling, with hard-coded constants, etc. is much more difficult to alter in useful ways

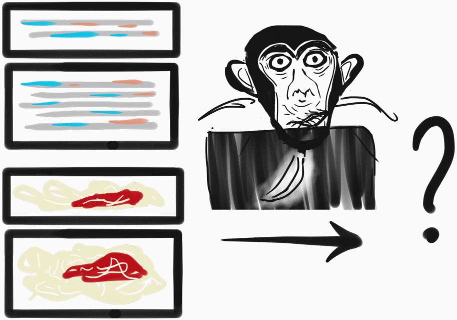


Figure 9: Spaghetti code and proper code might experience different distributions of outcomes from arbitrary changes to the software made by a junior developer from the local primate house.

Biological Perspective: Intraindividual Degeneracy

idea: employing a diverse collection of substructures that provide identical or near-identical functionality promote robustness through redundancy while providing many jumping off points for variation through repurposing or elaboration

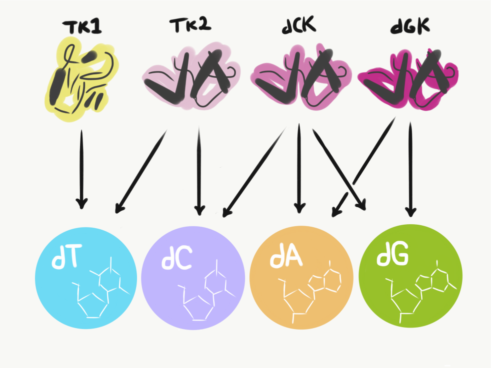
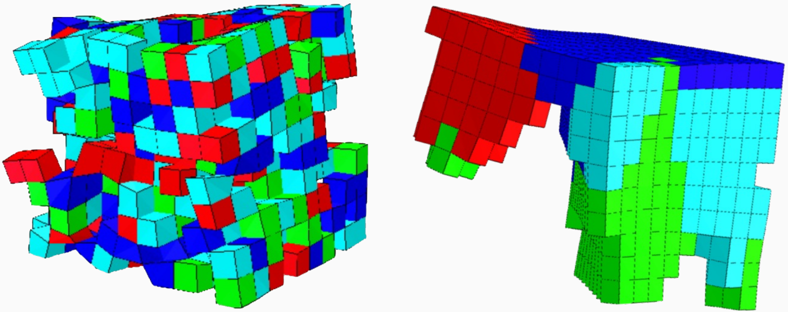


Figure 10: Mammalian deoxyribonucleoside kinases exhibit degeneracy [Sandrini and Piskur, 2005].

Evolvability in Action



(a) direct encoding (low regularity) (b) indirect encoding (high regularity)

Figure 11: Representative examples of soft robots evolved with direct and indirect representations [Cheney et al., 2013, Figures 6, 7]

Plasticity

Environmental Influence on the Phenotype

- in biology, genotype not sole determinant of phenotype
- $P = G + E$
- plasticity: phenotypic response to the environment
- direct plasticity versus indirect plasticity

Direct Plasticity: Biological Intuition

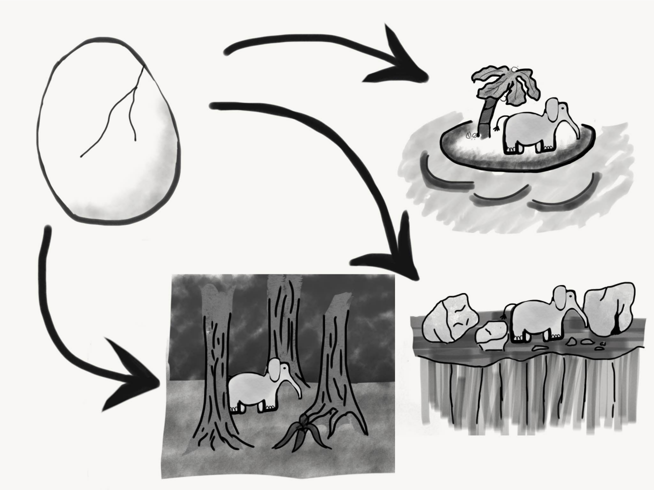


Figure 12: A cartoon illustration of resistance to environmental perturbation.

Indirect Plasticity: Biological Intuition

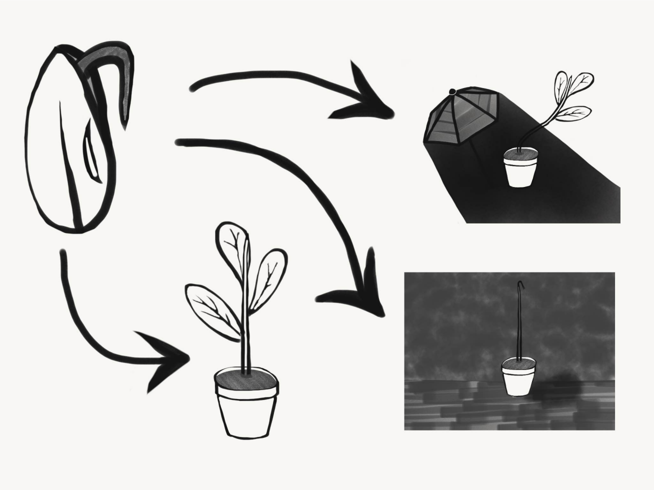


Figure 13: A cartoon illustration of alternate phenotypes expressed based on environmental signals.

Genetic Regulatory Network Model

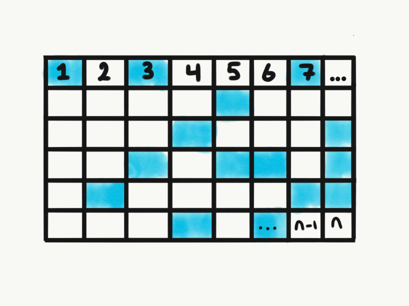


Figure 14: Chemical concentrations are represented as a list of boolean values.

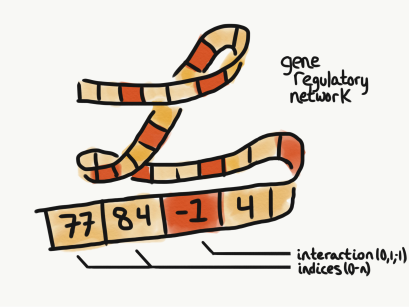
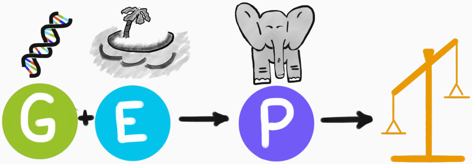
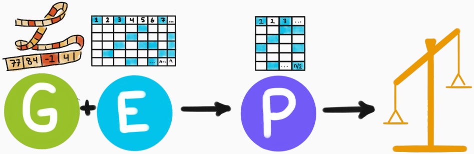


Figure 15: The GRN genotype is a set of if-then rules that acts on a set of chemical concentrations. The model employed was inspired by [Wilder and Stanley, 2015].

Model Framework



(a) biological inspiration

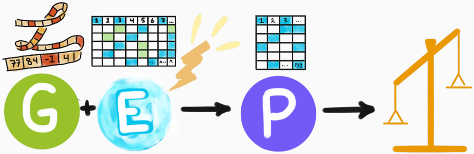


(b) genetic regulatory network model

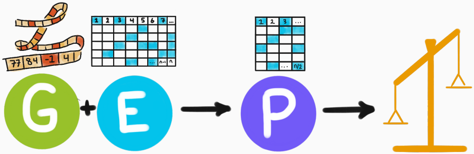
Figure 16: A comparison of the genetic regulatory network model and its biological inspiration.

Experiment: Direct Plasticity

Direct Plasticity: Initial State Perturbation



(a) experimental scheme



(b) control scheme

Figure 17: A comparison of the control and experimental schemes employed to investigate the relationship between direct plasticity and evolvability.

Evolvability Signature $P = 0$

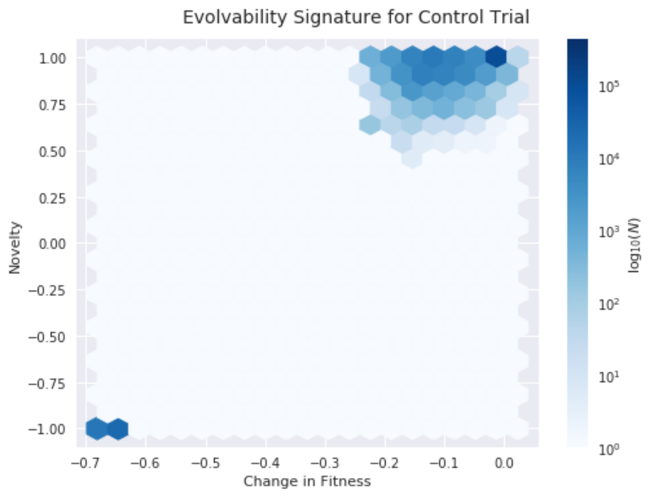


Figure 18: Evolvability signature of champion evolved with no initial plasticity. Figure after [Tarapore and Mouret, 2015].

Evolvability Signature $P = 0.1$

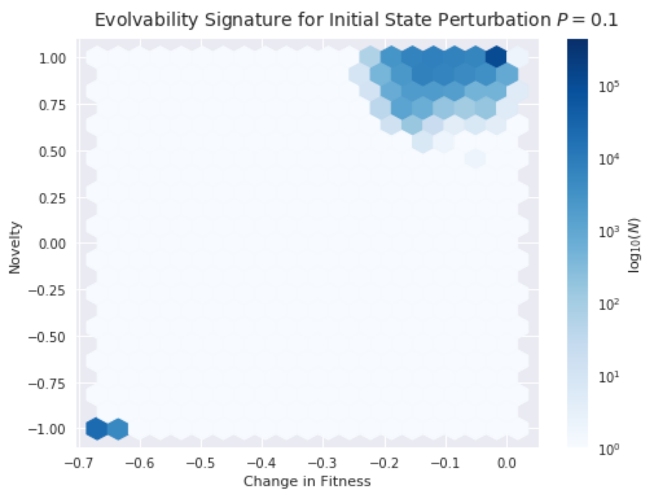


Figure 19: Evolvability signature of champion evolved with medium initial plasticity, $P = 0.1$. Figure after [Tarapore and Mouret, 2015].

Evolvability Signature $P = 0.2$

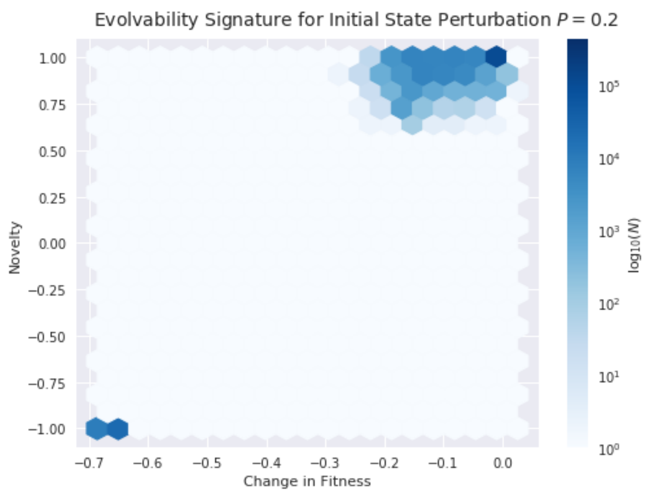


Figure 20: Evolvability signature of champion evolved with greater initial plasticity, $P = 0.2$. Figure after [Tarapore and Mouret, 2015].

Mutational Outcome Frequencies

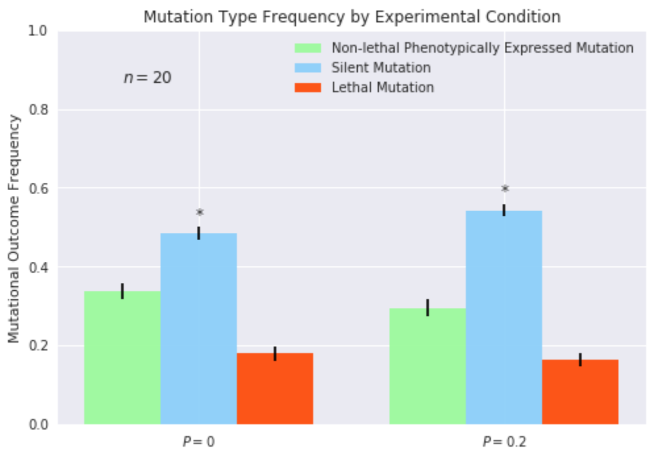


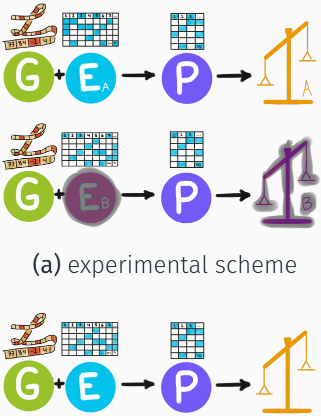
Figure 21: Comparison of mutational outcome frequencies for champions evolved with and without initial state perturbation.

Direct Plasticity Results: Summary

- direct plasticity increases robustness to mutation
- as in [Reisinger et al., 2005], repeated evaluations ($n = 10$) were required to observe impact of direct plasticity
- direct plasticity does not seem to promote canalization

Experiment: Indirect Plasticity

Indirect Plasticity: Conditional Initial State



(b) control scheme

Figure 22: A comparison of the control and experimental schemes employed to investigate the relationship between indirect plasticity and evolvability.

Evidence for Indirect Plasticity

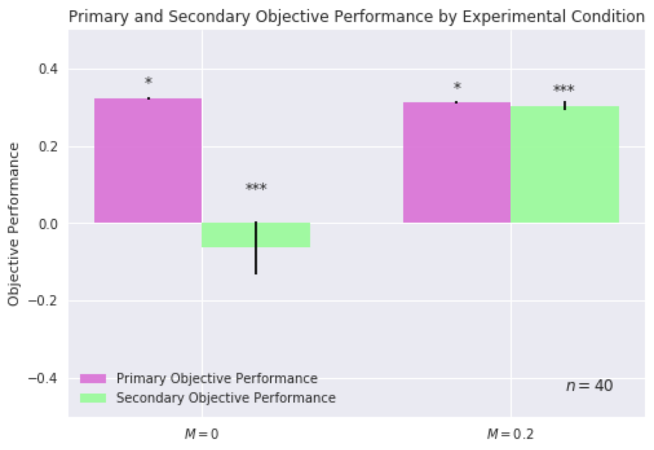


Figure 23: Comparison of objective performances of champions evolved with only primary condition/objective pair versus with both primary and secondary condition/objective pairs.

Evolvability Visualization $W = 0$

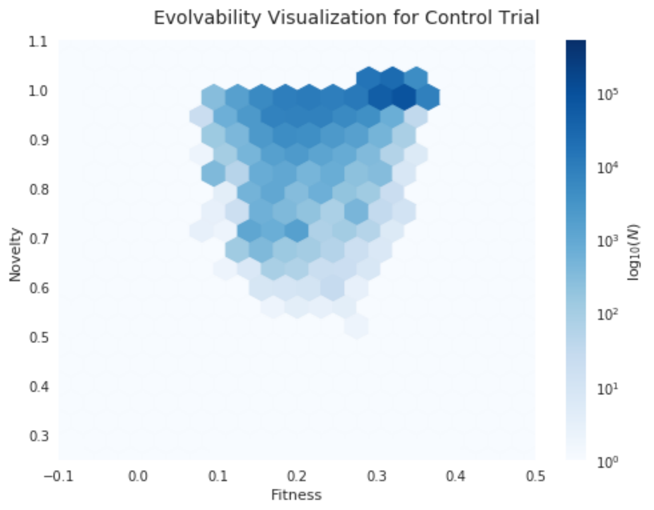


Figure 24: Evolvability visualization of champions evolved with only a primary condition/objective pair.

Evolvability Visualization $W = 0.2$

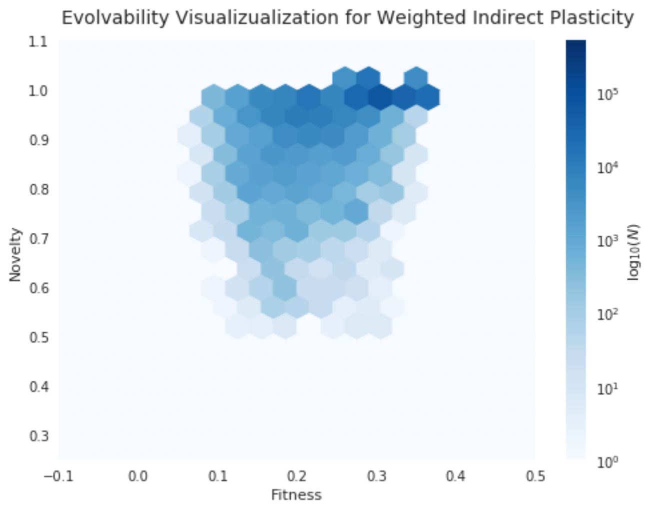


Figure 25: Evolvability visualization of champions evolved with primary and secondary condition/objective pairs.

Mutational Outcome Frequencies

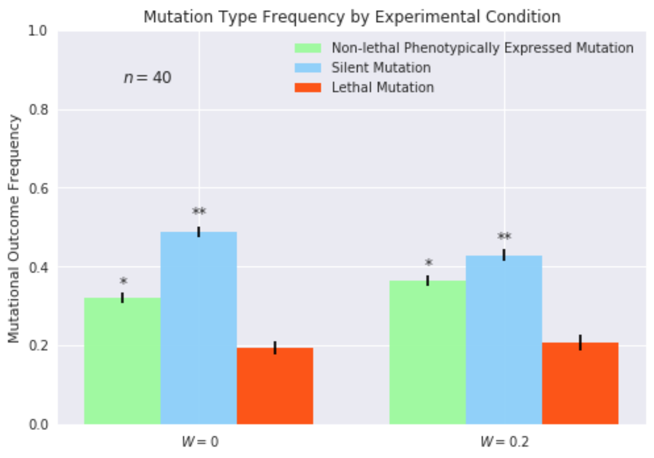
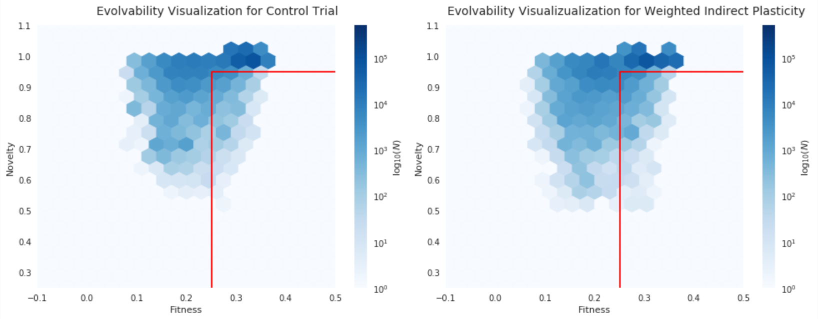


Figure 26: Comparison of mutational outcome frequencies for champions evolved with only primary condition/objective pair versus with both primary and secondary condition/objective pairs.

Frequency of Useful Novelty



(a) evolved with only primary condition/objective pair

(b) evolved with both primary and secondary condition/objective pairs

Figure 27: Comparison of evolvability visualizations with region corresponding to useful novelty highlighted.

Indirect Plasticity Results: Summary

- indirect plasticity observed
- indirect plasticity increases sensitivity to mutation
- indirect plasticity may promote useful novelty

Closing Thoughts

Next Steps

- investigate structural changes in gene regulatory networks induced by plasticity
- investigate interaction of direct and indirect plasticity
- attempt to demonstrate situation where search with plasticity outperforms search without

Closing Thoughts: Practical Applications

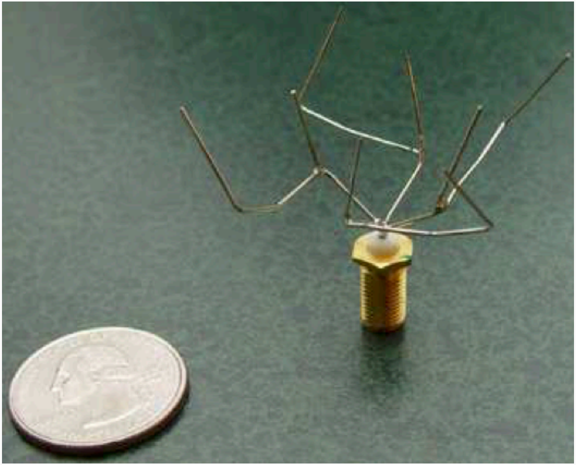


Figure 28: A spacecraft antenna design generated using evolutionary methods [Hornby et al., 2006, Figure 2(a)].

Closign Thoughts: Scientific Questions

- at what level of abstraction can the power of biological evolution be harnessed in a computational model?
- what are the fundamental mechanisms at play in evolution?

Closing Thoughts: Scientific Questions

- evolutionary biology provides continuing inspiration for new techniques in evolutionary computing
- evolutionary models move theory evaluation from a qualitative endeavor towards a quantitative endeavor

Acknowledgements

- DEAP [Fortin et al., 2012]
- Professor Richards for leading CS capstone
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- Professor Chambers for serving as my thesis advisor

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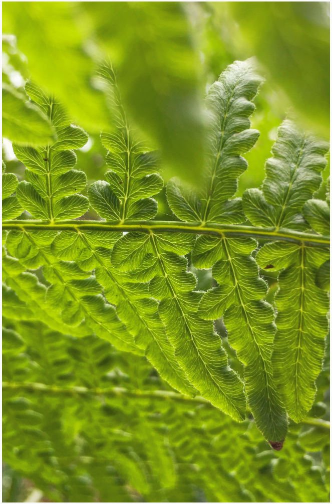

Questions?

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Complete Model

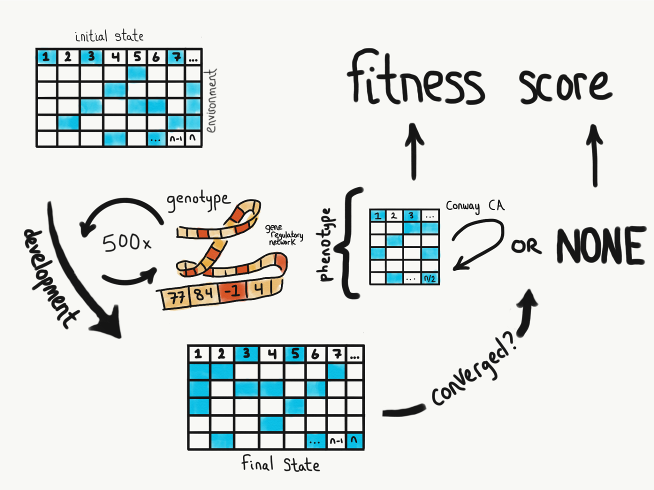


Figure 29: A cartoon overview of the development and assessment processes of the expanded model, based loosely on [Wilder and Stanley, 2015].

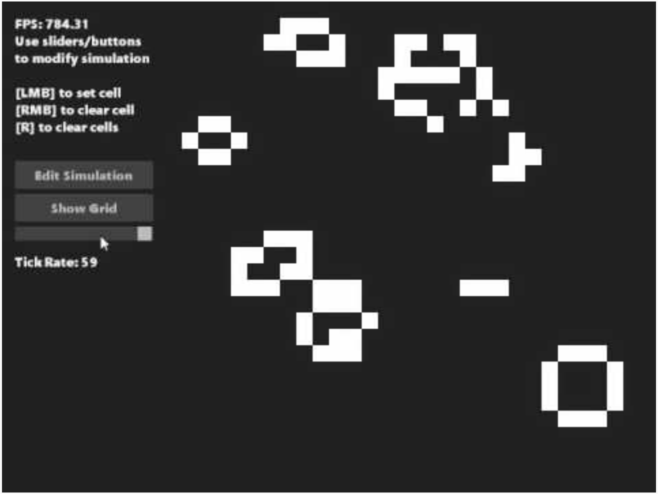


Figure 30: Video illustrations of Conway's Game of Life cellular automata in action.

Evidence for Indirect Plasticity

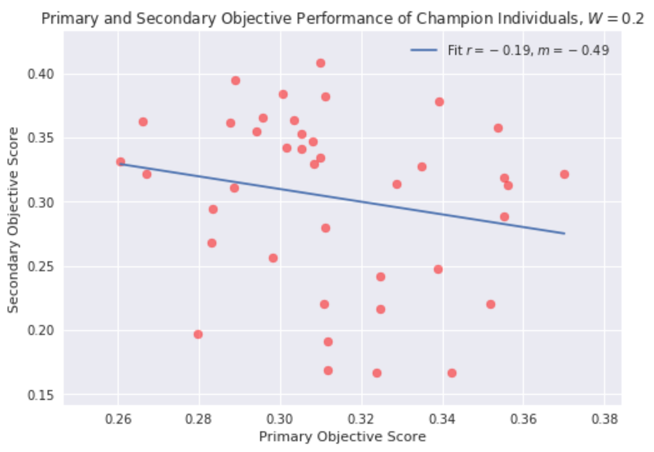


Figure 31: Primary and secondary objective performance of champion individuals evolved with primary and secondary condition/objective pair.

Evidence for Indirect Plasticity

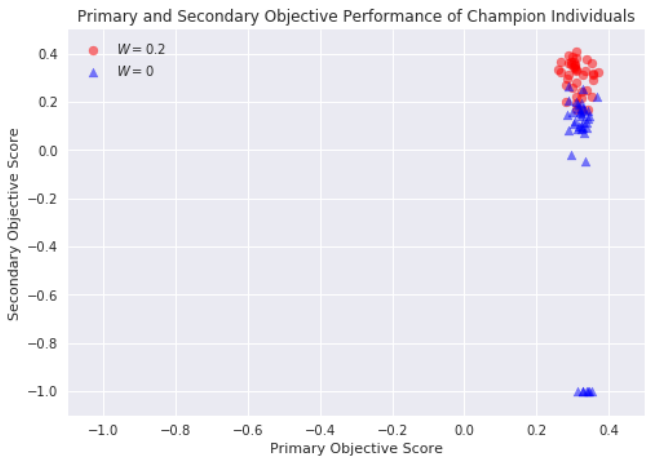
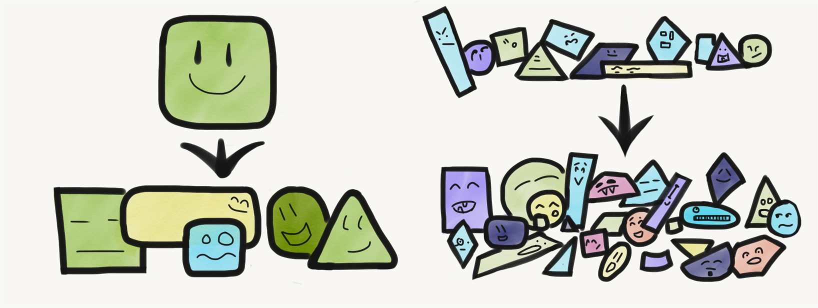


Figure 32: Comparison of objective performances of champions evolved with only primary condition/objective pair versus with both primary and secondary condition/objective pairs.

Evolvability as Novel Variation



(a) individual evolvability (b) population evolvability

Figure 33: An illustration contrasting individual and population evolvability [Wilder and Stanley, 2015].

Promoting Evolvability: Fitness Niches

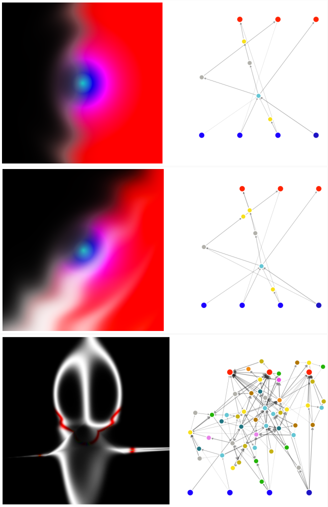


Figure 34: Illustration of compositional pattern producing networks (right) and their output images (left) generated via [Ha, 2015].

Promoting Evolvability: Fitness Niches

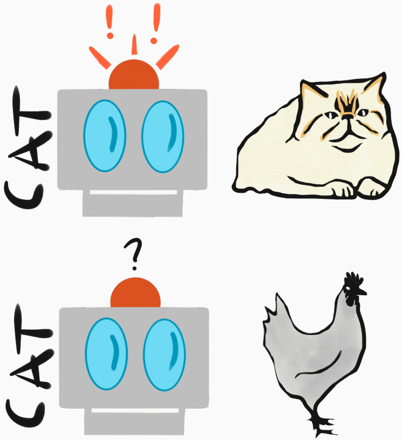


Figure 35: A deep neural network (DNN) is trained to recognize a specific category of images.

Promoting Evolvability: Fitness Niches

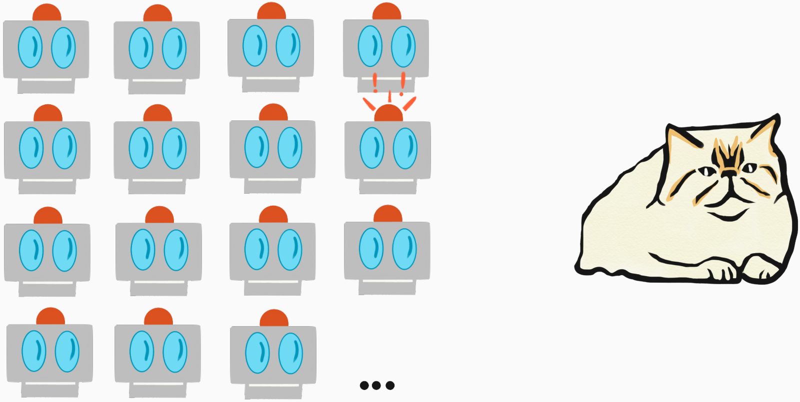


Figure 36: Several hundred fitness niches are defined using DNNs each trained to recognize different categories [Nguyen et al., 2015].

Promoting Evolvability: Fitness Niches

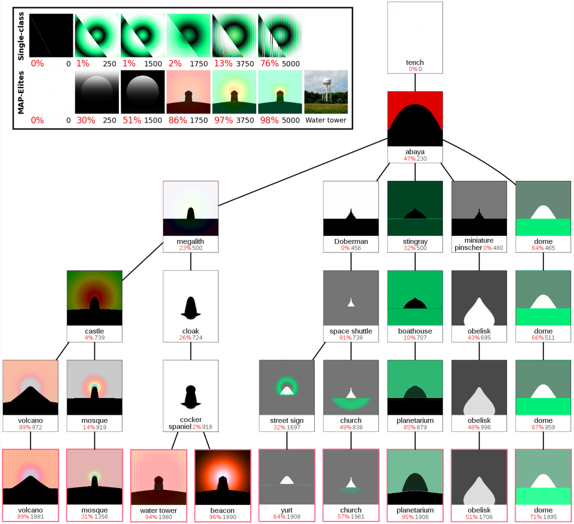


Figure 37: An illustration of goal-switching, where offspring from a parent that occupies one niche invade another [Nguyen et al., 2015, Figure 9]. Individuals that promote phenotypically variable offspring are rewarded [Mengistu et al., 2016].

Promoting Evolvability: Fitness Niches

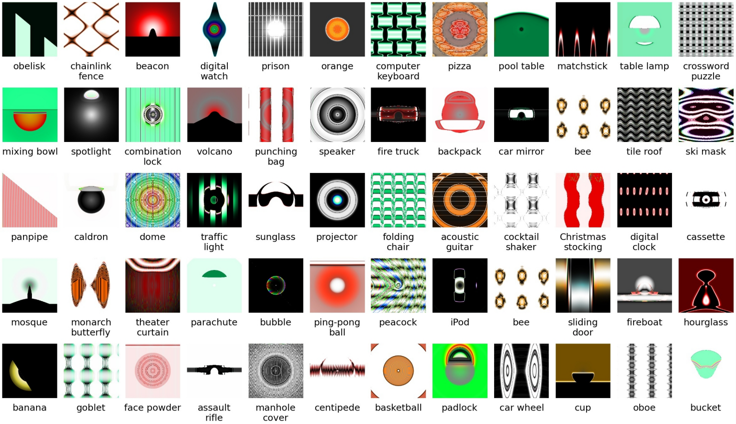


Figure 38: Selected champion individuals from a sample of environmental niches [Nguyen et al., 2015, Figure 7].