Investigating the Relationship Between Plasticity and Evolvability in a Genetic Regulatory Network Model

Math/CS Day

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April 29th, 2017

Background

Evolutionary Algorithm: Example

Figure 1: Evolution in Action [Cheney et al., 2013]

Evolutionary Algorithm: Problem Statement

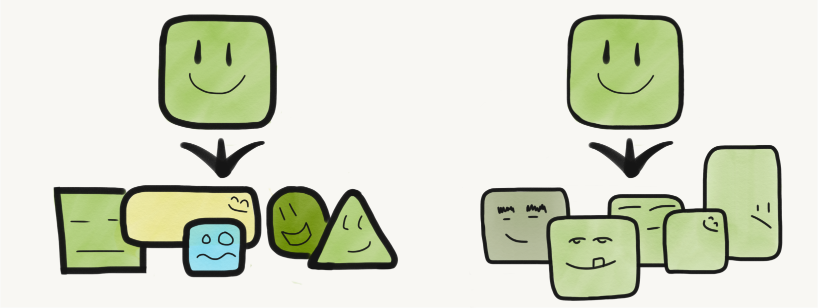
What makes an evolutionary algorithm work?

Defining Evolvability

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

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

Evolvability as Novel Variation



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

Figure 2: An illustration of individual evolvability, considering evolvability as heritable variation [Wilder and Stanley, 2015].

Evolvability as Bias towards Viable Variation

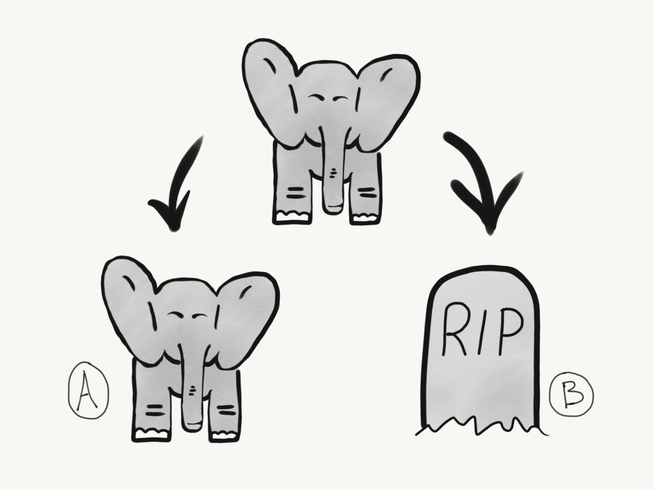


Figure 3: Illustration of robustness; high evolvability left and low evolvability right [Downing, 2015].

Objectives

Environmental Influence on the Phenotype

- in biology, genotype not sole determinant of phenotype
- $P = G + E$
- plasticity: phenotypic response to the environment
- how does environmental influence on the phenotype affect evolvability?

Motivation: Practical and Scientific

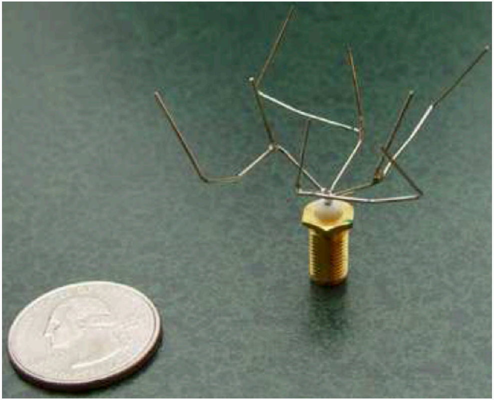


Figure 4: A spacecraft antenna design generated using evolutionary methods [Hornby et al., 2006, Figure 2(a)].

Figure 5: A biological frond design generated via evolution.

Genetic Regulatory Network Model

Model Framework

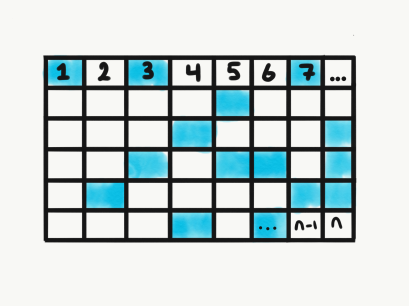


Figure 6: Chemical concentrations are represented as a list of boolean values.

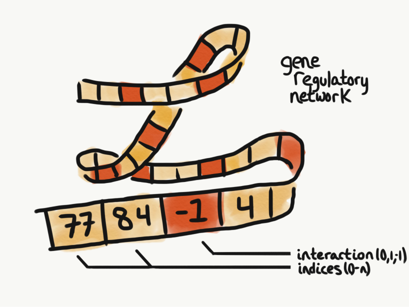
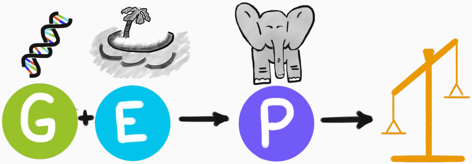
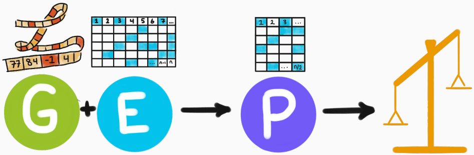


Figure 7: The GRN genotype is a set of if-then rules that acts on a set of chemical concentrations. The model employed was inspired by [Wilder and Stanley, 2015].



(a) biological inspiration

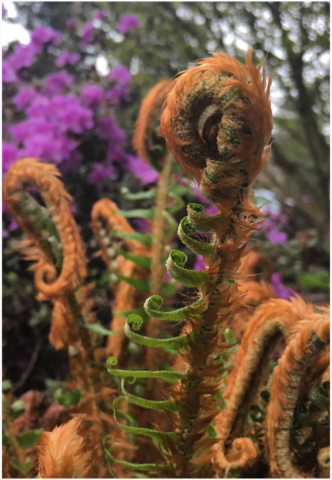


(b) genetic regulatory network model

Figure 8: A comparison of the genetic regulatory network model and its biological inspiration.

Model Implementation

- model implemented through DEAP (Distributed Evolutionary Algorithms in Python) framework [Fortin et al., 2012]
- experiments performed and analyzed on remote clusters using Jupyter notebook



Experiment: Direct Plasticity

Direct Plasticity: Biological Intuition

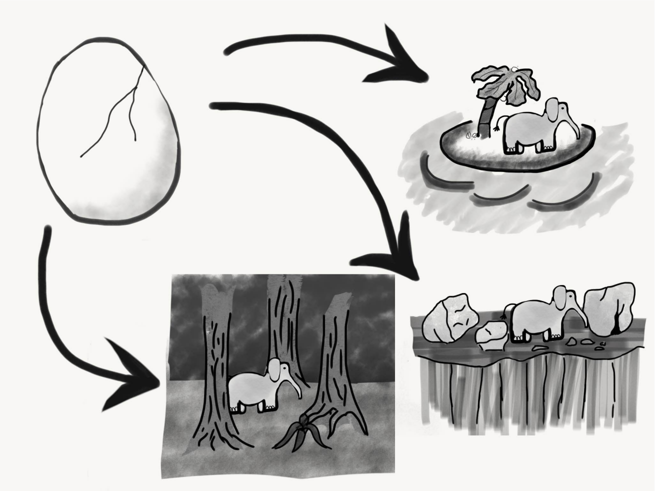
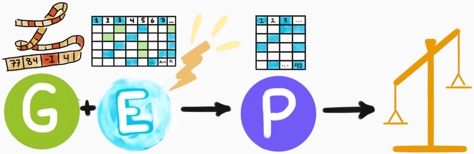
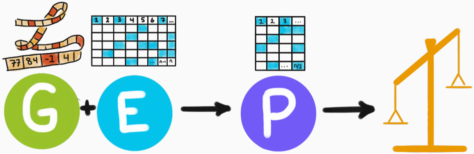


Figure 9: A cartoon illustration of resistance to environmental perturbation.

Direct Plasticity: Initial State Perturbation



(a) experimental scheme



(b) control scheme

Figure 10: A comparison of the control and experimental schemes employed to investigate the relationship between direct plasticity and evolvability.

Mutational Outcome Frequencies

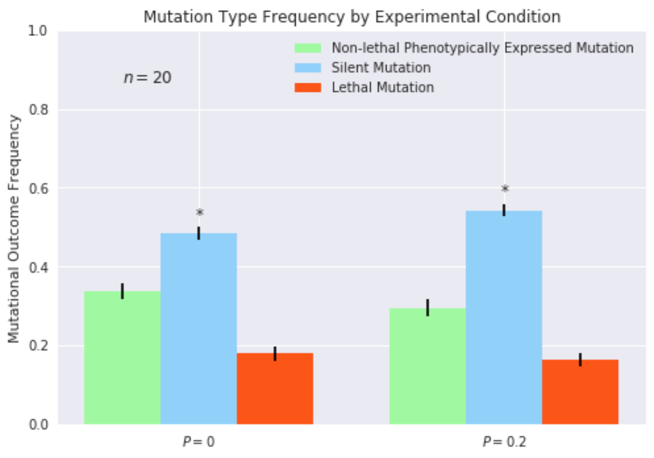


Figure 11: Comparison of mutational outcome frequencies for champions evolved with and without initial state perturbation.

Experiment: Indirect Plasticity

Indirect Plasticity: Biological Intuition

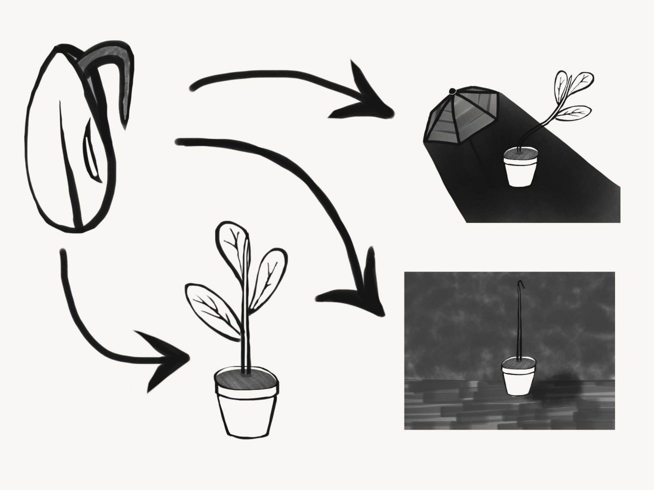
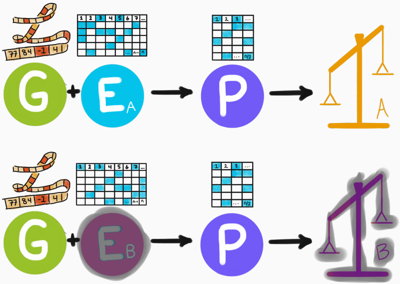
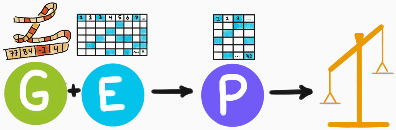


Figure 12: A cartoon illustration of alternate phenotypes expressed based on environmental signals.

Indirect Plasticity: Conditional Initial State



(a) experimental scheme



(b) control scheme

Figure 13: A comparison of the control and experimental schemes employed to investigate the relationship between indirect plasticity and evolvability.

Mutational Outcome Frequencies

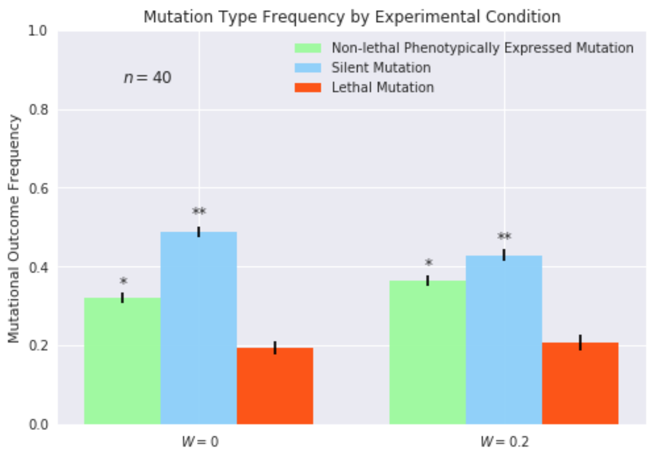
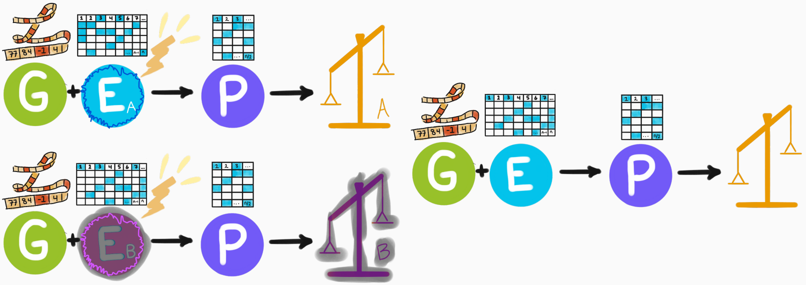


Figure 14: Comparison of mutational outcome frequencies for champions evolved with only primary condition/objective pair versus with both primary and secondary condition/objective pairs.

Experiment: Combined Plasticity

Combined Plasticity: Conditional Initial State with Perturbation



(a) experimental scheme

(b) control scheme

Figure 15: A comparison of the control and experimental schemes employed to investigate the relationship between combined plasticity and evolvability.

Mutational Outcome Frequencies

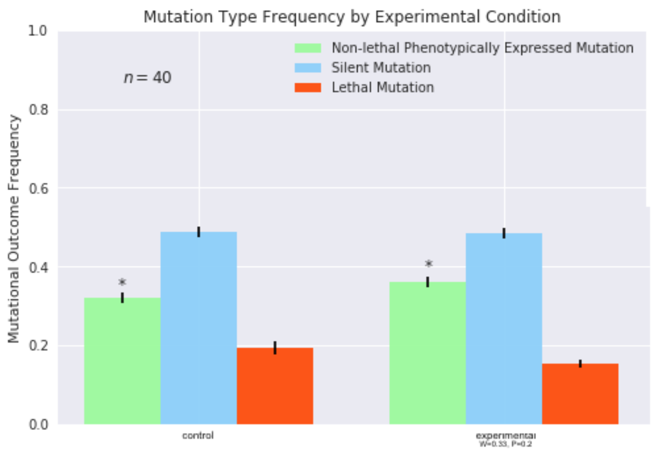


Figure 16: Comparison of mutational outcome frequencies for champions evolved with only primary condition/objective pair and no initial state perturbation versus with both primary and secondary condition/objective pairs and initial state perturbation.

Analysis

Analysis

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

Analysis

- environmental noise → noise mitigation structures → more silent mutations
- alternate phenotypic targets → developmental path switching structures → fewer silent mutations
- environmental noise and alternate phenotypic targets → …→ more nonlethal, expressed mutations

Closing Thoughts

Closing Thoughts: Challenges and Reflection

- data management
  - save data trial-wise instead of batch-wise
  - export to standard format
- Jupyter notebooks
  - write frequently used analysis functions into package
- compute time
  - seek grant funding for more stable compute environment

Closing Thoughts: Next Steps

- more directly biologically-inspired model
- attempt to demonstrate situation where search with plasticity outperforms search without

Acknowledgements

- DEAP [Fortin et al., 2012]
- Professor Richards for leading CS capstone
- Professor Chiu and Chili Johnson for lending me compute time
- Professors Smith and Chambers for serving as my thesis committee

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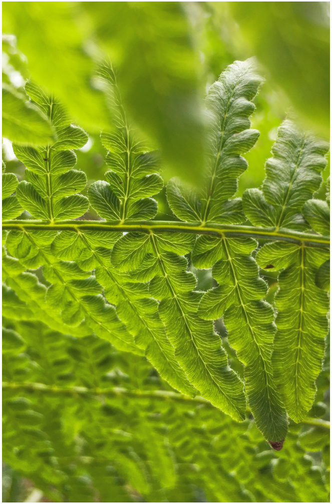

Questions?

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