

Evolvability: What is It and How Do We Get It?

Coolidge Otis Chapman Honors Program

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Evolutionary Algorithm



"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
- \cdot this is called search

Evolutionary Algorithm

- individual
- \cdot population
- fitness function
- \cdot selection
- mutation
- genotype
- \cdot phenotype



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

Evolutionary Algorithm

Figure 2: Evolution in Action [Cheney et al., 2013]

What makes an evolutionary algorithm work?

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

Evolvability as Bias towards Useful Variation



Figure 4: Illustration of developmental constraint; high evolvability left and low evolvability right [Smith et al., 1985, Tuinstra et al., 1990].

Evolvability as Bias towards Useful Variation



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

Organizing and Analyzing Factors that Promote Evolvability

Proximate/Ultimate Thinking



Figure 6: Why is the flower purple? Proximate and ultimate explanations differ [Wilson, 2007].

Proximate Causality

 \cdot describes specific organismal processes or structures

Intermediate Causality

• describes characteristics of an organism as a whole

Ultimate Causality

 describes the relation between the individual and its environment

Proximate/Intermediate/Ultimate Organization

Proximate Causality

- duplication and divergence
- developmental constraint
- hidden genetic variation
- exploratory growth
- weak linkage
- indirect encodings

Intermediate Causality

- modularity
- robustness
- canalization
- plasticity
- intraindividual degeneracy
- interindividual degeneracy
- regularity

Ultimate Causality

- temporally varying goals
- environmental influence on phenotype
- fitness degeneracy

Proximal Causality: Developmental Constraint

idea: the phenotype results from development, so developmental processes influence the phenotypic outcomes of mutation



Figure 7: Illustration of Canalization Against Bilateral Asymmetry in Drosophilia melangoster [Tuinstra et al., 1990].

Intermediate Causality: Intraindividual Degeneracy

idea: employing a diverse collection 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 8: Mammalian deoxyribonucleoside kinases exhibit degeneracy [Sandrini and Piskur, 2005].

Ultimate Causality: Modularly Varying Fitness Function

idea: if evolution sets a moving target, organisms that produce variable offspring will be selected for



(a) low individual evolvability

(b) high individual evolvability

Figure 9: An hypothetical illustration of a modularly varying fitness function [Kashtan and Alon, 2005].

Analysis

observations:

- proximal and intermediate causality relates to the genotype-phenotype mapping
- ultimate causality is related to interaction with the environment to determine fitness

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paths forward:

- taking a broader view of fitness and selection
- taking a more nuanced view of the developmental process

Evolvability in Action

Promoting Evolvability: Indirect Encoding



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

Figure 10: Representative examples of soft robots evolved with direct and indirect representations [Cheney et al., 2013, Figures 6, 7]



Figure 11: Illustration of compositional pattern producing networks (right) and their output images (left) generated via [Ha, 2015].



Figure 12: A deep neural network (DNN) is trained to recognize a specific category of images.



Figure 13: Several hundred fitness niches are defined using DNNs each trained to recognize different categories [Nguyen et al., 2015].



Figure 14: 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].



Figure 15: Selected champion individuals from a sample of environmental niches [Nguyen et al., 2015, Figure 7].

Closing Thoughts

Practical Applications



Figure 16: A spacecraft antenna design generated using evolutionary methods [Hornby et al., 2006, Figure 2(a)].

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?



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



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Questions?

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