Evolvability in EANN

Northwest Honors Research Symposium

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Motivation

Bio AI

- tasks that are easy for people can be very difficult for computers
- idea: use algorithms inspired by biological structures and processes

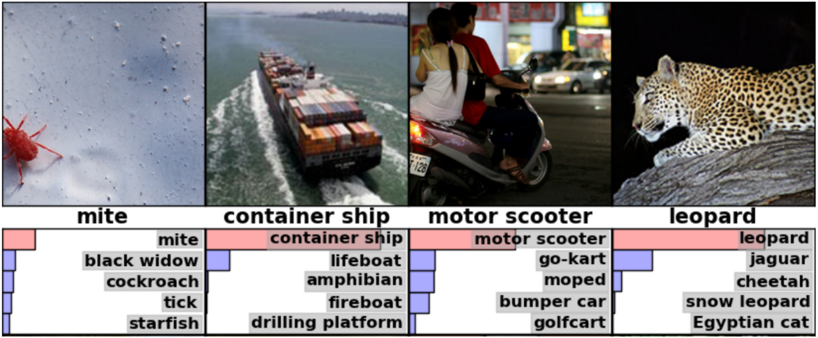


Figure 1: TensorFlow Image Identification [Ima,]

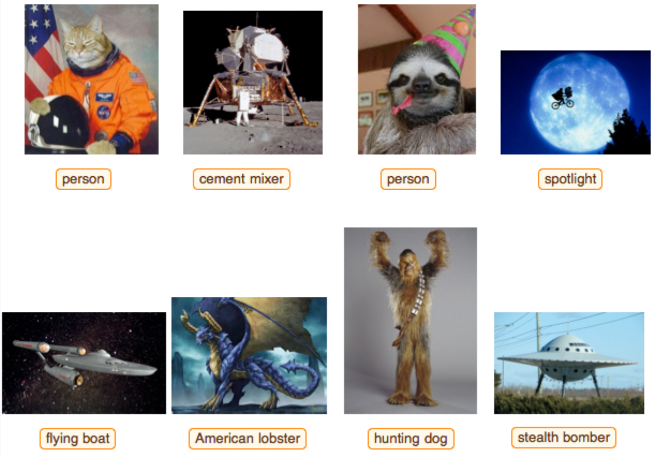


Figure 2: Amusing responses to unexpected images from the Wolfram Image Identification Project [Wolfram, 2015]

Bio AI

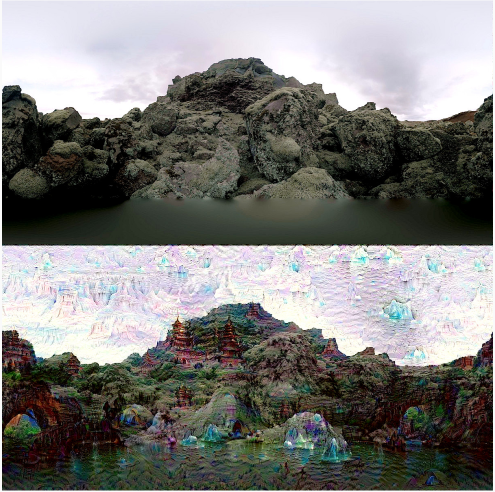


Figure 3: Google Deep Dream [Mordvintsev et al., 2015a]

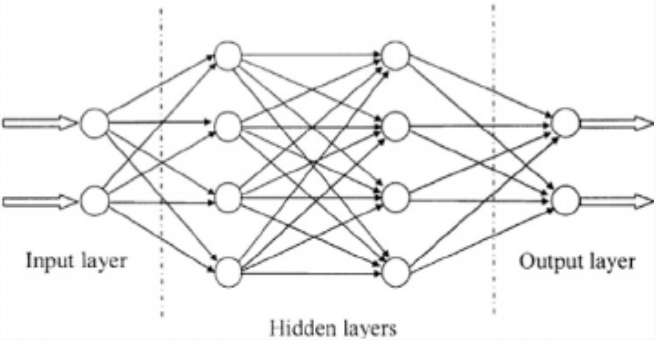


Figure 4: Schematic diagram of an Artificial Neural Network (ANN) [Ata, 2015, Figure 1]

Evolutionary Algorithms

Evolutionary Algorithms

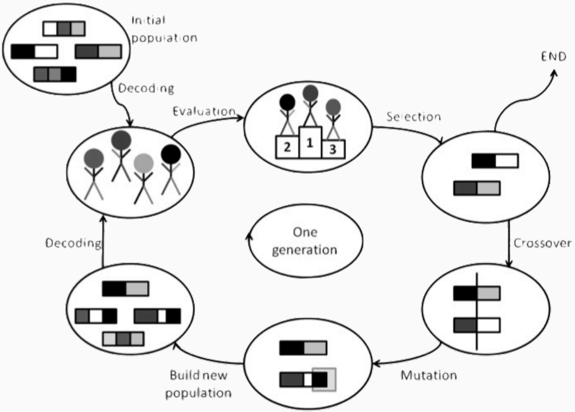


Figure 5: Schematic illustration of the evolutionary algorithm [Prothmann et al., 2009, Figure 1]

Evolutionary Algorithms

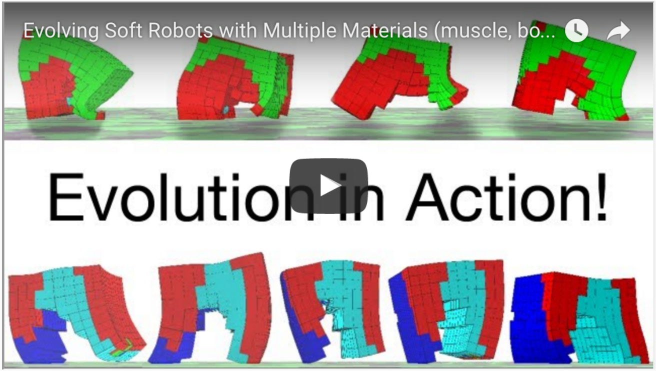


Figure 6: Evolution in Action [Cheney et al., 2013]

Evolutionary Algorithms: Glossary

- individual
- population
- fitness function
- selection
- recombination
- genotype
- phenotype

Evolutionary Algorithms: Problem Statement

What makes an evolutionary algorithm work?

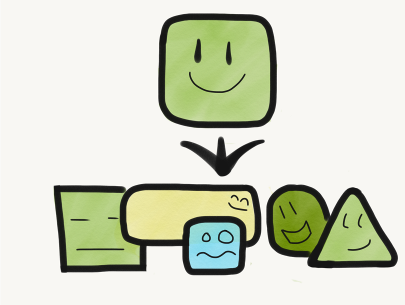
Defining Evolvability

Defining Evolvability

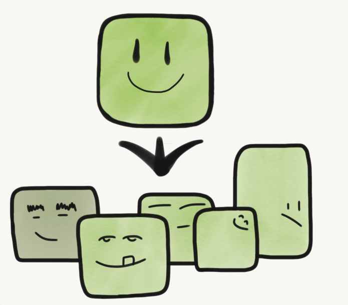
consensus: the amount of useful variation generated by the evolutionary process

- evolvability as the ability to generate heritable variation
- evolvability as bias towards useful variation

Evolvability as Heritable Variation



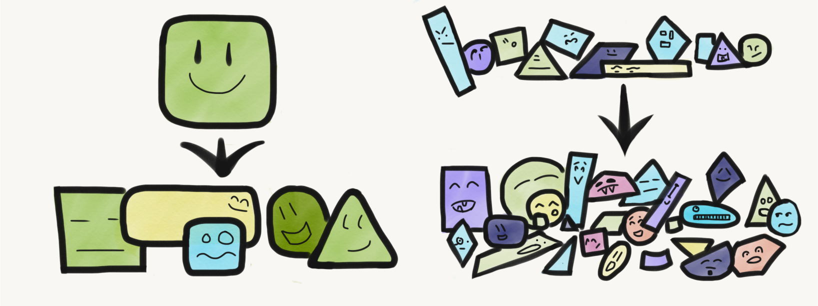
(a) high individual evolvability



(b) low individual evolvability

Figure 7: An illustration of individual evolvability, considering evolvability as heritable variation [Wilder and Stanley, 2015].

Evolvability as Heritable Variation



(a) individual evolvability (b) population evolvability

Figure 8: An illustration contrasting individual and population evolvability [Wilder and Stanley, 2015].

Evolvability as Bias towards Useful Variation

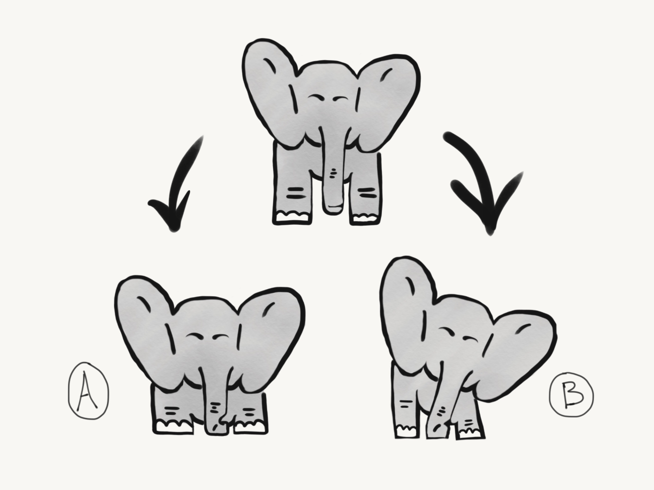


Figure 9: Illustration of developmental constraint; high evolvability left and low evolvability right [Smith et al., 1985, Tuinstra et al., 1990].

Evolvability as Bias towards Useful Variation

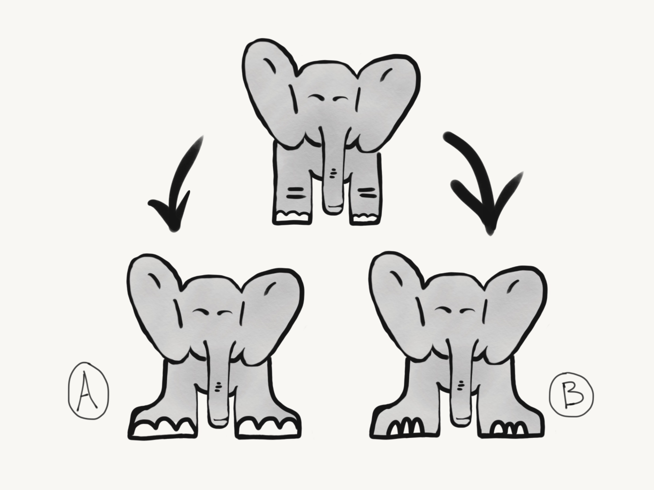


Figure 10: Illustration of exploratory growth; high evolvability left and low evolvability right [Downing, 2015].

Evolvability as Bias towards Useful Variation

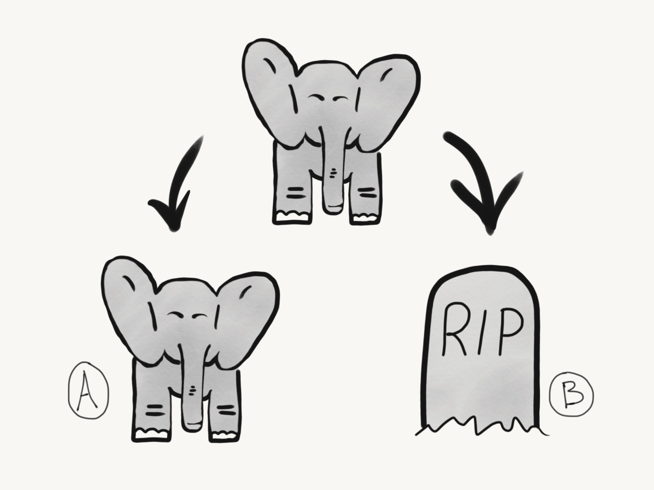
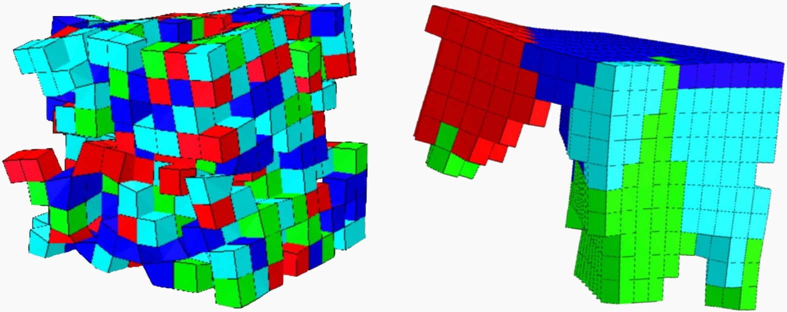


Figure 11: Illustration of robustness; high evolvability left and low evolvability right [Downing, 2015].

Promoting Evolvability

Promoting Evolvability: Indirect Representation



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

Figure 12: Representative examples of soft robots evolved with direct and indirect representations [Cheney et al., 2013, Figures 6, 7]

Promoting Evolvability: Selection Pressure

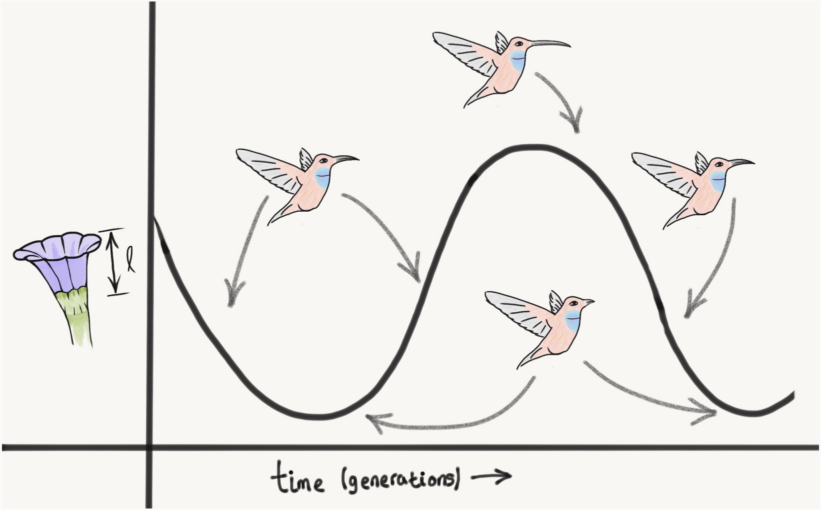


Figure 13: An illustration of a modularly varying fitness function [Kashtan and Alon, 2005]

Promoting Evolvability in EANN

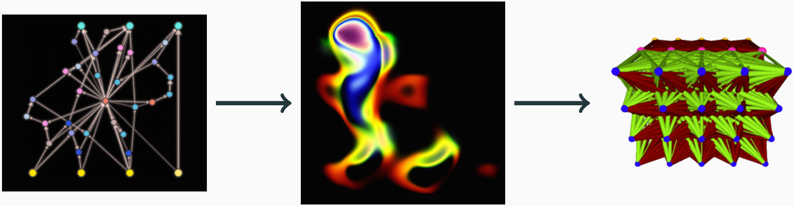


Figure 14: The working principle of HyperNEAT indirect genetic encoding; the genotype, a Compositional Pattern Producing Network (left), is used to construct a neural network configuration (right) [Ha, 2015], [Clune et al., 2011, Figure 15]

Novelty Search

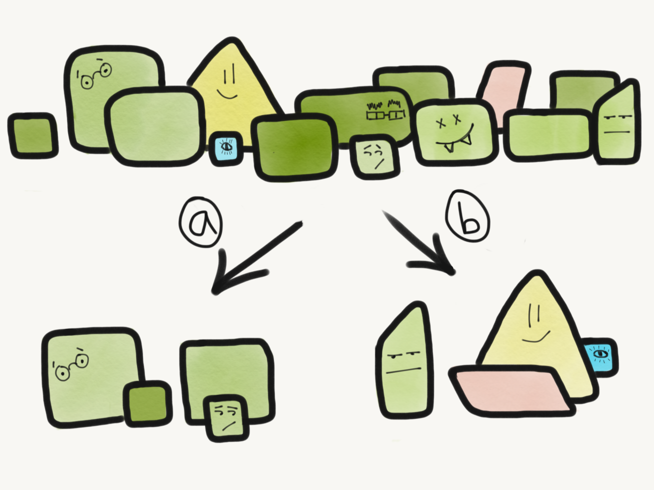


Figure 15: Novelty search, an example of divergent selection [Wilder and Stanley, 2015]

Conclusion

Closing Thoughts

Potential Applications

- robotic control [Fehérvári and Elmenreich, 2010]
- financial trading [Sher, 2011]
- long term: more general artificial intelligence? [Downing, 2015, pg 364]

Scientific Questions

- what are the fundamental mechanisms at play in cognition and evolution?

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Questions?

References I

- Image Recognition.
- Ata, R. (2015).
  Artificial neural networks applications in wind energy systems: a review.
  Renewable and Sustainable Energy Reviews, 49:534–562.
- Cheney, N., Maccurdy, R., Clune, J., and Lipson, H. (2013).
  Unshackling Evolution: Evolving Soft Robots with Multiple Materials and a Powerful Generative Encoding.
- Clune, J., Stanley, K. O., Pennock, R. T., and Ofria, C. (2011).
  On the performance of indirect encoding across the continuum of regularity.
  IEEE Transactions on Evolutionary Computation.

References II

Downing, K. L. (2015).
Intelligence emerging : adaptivity and search in evolving neural systems.
MIT Press, Palatino.

Fehérvári, I. and Elmenreich, W. (2010).
Evolving Neural Network Controllers for a Team of Self-Organizing Robots.
Journal of Robotics, 10.

Gatys, L. A., Ecker, A. S., and Bethge, M. (2015).
A Neural Algorithm of Artistic Style.

Ha, D. (2015).
Neurogram.

References III

Kashtan, N. and Alon, U. (2005).
Spontaneous evolution of modularity and network motifs.
PNAS, 102(39):13773–13778.

Mordvintsev, A., Olah, C., and Tyka, M. (2015a).
DeepDream - a code example for visualizing Neural Networks.

Mordvintsev, A., Olah, C., and Tyka, M. (2015b).
Inceptionism: Going Deeper into Neural Networks.

Prothmann, H., Schmeck, H., and Schmeck, H. (2009).
Evolutionary algorithms for traffic signal optimisation.
In *Proceedings of mobil.TUM 2009 - International Scientific Conference on Mobility and Transport*. TU München.

References IV

Reisinger, J., Stanley, K. O., and Miikkulainen, R. (2005).
Towards an Empirical Measure of Evolvability.
GECCO'05 Proceedings.

Sher, G. I. (2011).
Evolving Chart Pattern Sensitive Neural Network Based Forex Trading Agents.

Smith, J. M., Burian, R., Kauffman, S., Alberch, P., Campbell, J., Goodwin, B., Lande, R., Raup, D., and Wolpert, L. (1985).
Developmental Constraints and Evolution: A Perspective from the Mountain Lake Conference on Development and Evolution The Quarterly Review of Biology.
The Quarterly Review of Biology, 60(3):265–287.

References V

Tuinstra, E., De Jong, G., and Scharloo, W. (1990).
Lack of response to family selection for direction asymmetry in Drosophila melanogaster: left and right are not distinguished during development.
Proc. R. Soc. Lond. B, 241(1301):146–152.

Wilder, B. and Stanley, K. (2015).
Reconciling explanations for the evolution of evolvability.
Adaptive Behavior, 23(3):171–179.

Wolfram, S. (2015).
Wolfram Language Artificial Intelligence: The Image Identification Project.