Evolutionary Computation

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1 Abstract

2 Introduction

2.1 Background

Biomimicry, the imitation of nature for solving human problems has produced many examples of world class design. Some great examples of Biomimicry are Velcro(R), self-cleaning paints and Shinkansen high-speed trains[**?**]. In particular these examples imitate the form of nature's physical systems. Since the term biomimicry was first coined in 1997, this design philosophy has started to inspire new developments in various subjects such as the circular economy in product design[CITE] as well as several pieces of ongoing work in Computer Science such as self-driving cars[CITE]. Life has been around on earth for 3.8 billion years, this is a lot of R&D time to produce useful solutions which can be related to many of the current problems in various fields[CITE, VOX video].
Clearly Evolutionary Computation is an optimisation process inspired by nature in this way.

2.2 EC for Snake

building on previous work in this area[**?**, **?**].
The game itself features elements of stochasticity. In a given round the snake's food might spawn in a number of random places. This adds an additional level of difficulty to the problem as the fitness of a given algorithm may change on each run. One option to get around this could be to perform the fitness evaluation on multiple plays of the game in order to get a more fair [] of how the algorithm performs overall.

3 Methods

3.1 Representation

3.1.1 Available Options

Representation options: Genetic Algorithms Evolutionary Programming Evolutionary Strategy
Genetic Programming ¡—– ??? Typing? Strong/Weak?
Grammatical Evolution? Is this explicitly supported in DEAP? DEAP's transparency allows virtually any algorithm to be implemented but it's easier to use the built in structures.

3.1.2 Choice and Justification

3.1.3 Physical Environments

Which additional sensing functions (if any) have been implemented? Additional functions may help the snake to find a better solution, however we need to be careful of overparameterising the problem. This is a common trade-off in many forms of machine learning?

3.1.4 Initialisation Procedure

3.2 Population and Evaluation

3.2.1 General Discussion

3.2.2 Parent Selection

3.2.3 Maintaining Diversity

Within evolutionary computation, the simulations individuals correspond to.. A diverse population is, by definition, exploring more of the search space than one that is not.
Textbook: 'Premature convergence is the well-known effect of losing population diversity too quickly and getting trapped in a local optimum.'
Diversity is difficult to quantity in an objective manner and, as such, no single measure for it exists[].
Textbook: some options are: no. phenotypes/genotypes, no. different fitness values
In biological evolution, old generations die to free up resources for newer generations. Disregarding solutions due to age ...
Parent Selection can be random, so (if this is the case) good solutions may well die out.

3.2.4 Bloat

Bloat, the increase of a program size without significant increase in fitness, is a difficult problem to overcome. Bloat is linked (but different) to overfitting, a common problem in many forms of machine learning[**?**].
Several recent papers discuss this issue and propose methods for tackling it[**?**, **?**]. The two main solutions to bloat are parsimony pressure and double tournaments.
[**?**]
It has been shown that the order of a double tournament has no significant bearing on the end result. [cite, practical?]

3.3 Variation Operators

3.3.1 Mutation

3.3.2 Recombination

3.3.3 Termination Condition

4 Results

4.0.1 Calibration

5 Conclusion

5.1 Main Findings

5.2 Further Work

6 References

[1] J. B. Tenenbaum *et al.*, “A global geometric framework for nonlinear dimensionality reduction,” *Science*, vol. 290, pp. 2319 – 2323, 2000.

[2] M. Belkin and P. Niyoji, “Laplacian eigenmaps for dimensionality reduction and data representation,” *Neural Computation*, vol. 15, pp. 1373 – 1396, 2003.

[3] X. He and P. Niyogi, “Locality preserving projections,” *Advances in Neural Information Processing Systems*, vol. 16, pp. 153 – 160, 2003.

[4] M. Fiedler, “Algebraic connectivity of graphs,” *Czechoslovak Mathematical Journal*, vol. 23, no. 2, p. 298 305, 1973.

[5] M. Balasubramanian and E. L. Schwartz, “The isomap algorithm and topological stability,” *Science*, vol. 295, p. 7, 2002. [Online]. Available: http://science.sciencemag.org/content/295/5552/7

[6] H. Gruhn and P. Persson, “Towards a robust algorithm for distributed monitoring of network topology changes,” in *2014 13th Annual Mediterranean Ad Hoc Networking Workshop (MED-HOC-NET)*, June 2014, pp. 1–7.

[7] X. Wang, Y. Koç, R. E. Kooij, and P. Van Mieghem, “A network approach for power grid robustness against cascading failures,” in *Reliable Networks Design and Modeling (RNDM), 2015 7th International Workshop on.* IEEE, 2015, pp. 208 – 214.

[8] T. Hastie *et al.*, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2nd ed. Springer Science Business Media, LLC, 2009.

[9] C. K. Williams, “On a connection between kernel pca and metric multidimensional scaling,” in *Advances in neural information processing systems*, 2001, pp. 675–681.

[10] K. A. Stroud, *Engineering Mathematics*, 5th ed. Palgrave, 2001.

[11] M. P. Dickens, W. A. P. Smith, J. Wu, and E. R. Hancock, *Face Recognition Using Principal Geodesic Analysis and Manifold Learning.* Berlin, Heidelberg: Springer, 6 2007, pp. 426 – 434.

[12] M.-H. Yang, "Face recognition using extended isomap," in *Proceedings. International Conference on Image Processing*, vol. 2, 9 2002, pp. II–117–II–120 vol.2.

[13] W. Yu, X. Teng, and C. Liu, "Face recognition using discriminant locality preserving projections," *Image and Vision Computing*, vol. 24, no. 3, pp. 239 – 248, 2006. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0262885605002039

[14] X. He *et al.*, "Face recognition using laplacianfaces," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 27, no. 3, pp. 328–340, March 2005.

[15] Y. Bengio, J.-F. Paiement, and P. Vincent, "Out-of-sample extensions for lle, isomap, mds, eigenmaps, and spectral clustering," in *In Advances in Neural Information Processing Systems.* MIT Press, 2003, pp. 177–184.

7 Appendix