The Effects of Lifetime Learning on the Diversity and Fitness of Populations

Dara Curran
Computer Science Dept.
University College Cork,
Ireland
d.curran@cs.ucc.ie

Colm O'Riordan
Computer Science Dept.
National University of Ireland,
Galway
colm.oriordan@nuigalway.ie

Humphrey Sorensen
Computer Science Dept.
University College Cork,
Ireland
sorensen@cs.ucc.ie

Category: Computing Methodologies: ARTIFICIAL INTELLIGENCE: Learning
General Terms: Experimentation
Keywords: Lifetime Learning, Diversity, Evolutionary Learning

1. INTRODUCTION

Much artificial intelligence research has focused on the interaction between learning and evolution, where individuals within a population of artificial organisms are capable of evolving genetically and also of acquiring knowledge during their lifetime. The aim of this paper is to examine whether diversity can be maintained by lifetime learning.

2. RELATED WORK

Evolutionary learning refers to the process whereby a population of organisms evolves, or learns, by genetic means through a Darwinian process of iterated selection and reproduction of fit individuals.

Hinton and Nowlan employed a genetic algorithm to study the effects of lifetime learning on the performance of genetic evolution [1]. Each agent in the model possesses a genome, comprised of a string of characters which can be one of 1, 0 or *?*. Each agent is allowed a number of rounds of lifetime learning where for each *?* in the genotype they 'guess' its value, assigning it either a 1 or a 0.

Experimental results showed that, once learning was applied, the population converged on the problem solution, showing that individual learning is capable of guiding genetic evolution.

3. MODEL

Our model follows the structure of the original Hinton and Nowlan experiments. Where a population evolves solely by evolutionary learning, agent genomes consist of strings of 1s or 0s. Populations employing lifetime learning have genomes containing 1s, 0s or ?s, where the ?s represent the agent's phenotypic ability to guess either 1 or 0.

Our model employs the NK fitness model as the fitness landscape for the experiments [2]. Unlike the previous model, the NK fitness model provides some evolutionary feedback to populations evolving genetically and thus allows a more meaningful comparison between population and lifetime learning.

GECCO'07, July 7–11, 2007, London, England, United Kingdom.
ACM 978-1-59593-697-4/07/0007.

3.1 Fitness calculation

Populations employing purely genetic evolution possess genomes comprising of 1s or 0s (no ?s) and therefore have no opportunity to alter the way they interact with their environment. The fitness of agents in such populations is measured directly from their genomes.

When a population adds lifetime learning to evolutionary learning, its members are given the opportunity to replace each of the ?s in their genomes with either 1s or 0s. Each agent guesses the value of its ? with equal probability. Each guess is evaluated using the fitness function and an agent's best guess is taken as its fitness value.

3.2 Diversity measure

The diversity measure examines the differences between members of a population. Diversity is defined as the average of all individual Hamming distances between phenotypes of individuals x and y, $h(x, y)$, whose phenotypes are unique within the population.

$$\frac{2}{n(m-1)} \sum_{x=1}^{m} \sum_{y=x+1}^{m} h(x, y)$$

4. EXPERIMENTS

The experiments employ populations endowed with evolutionary learning alone and populations employing both evolutionary and lifetime learning. Both fitness and diversity are measured for each experiment. Populations of 1000 agents are allowed to evolve to 400 generations.

The results obtained provide a further confirmation that combining lifetime learning with evolutionary learning leads to an increase in fitness. In addition, our results show that lifetime learning maintains higher diversity levels than evolutionary learning alone.

Acknowledgements

The first author would like to acknowledge the support of the Irish Research Council for Science, Engineering and Technology.

5. REFERENCES

[1] G. E. Hinton and S. J. Nowlan. How learning guides evolution. *Complex Systems*, 1:495–502, 1987.
[2] S. A. Kaufmann. Adaptation on rugged fitness landscapes. *Lectures in the Sciences of Complexity*, 1:527–618, 1989.