Behavioural Genetics inspired framework for Neuro-evolution

Knowledge Lab

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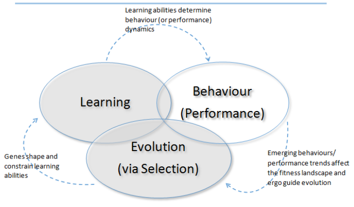

Figure 1: Interactions between evolution and learning

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Approach

Despite the benefits of neuro-evolutionary approaches, the process of designing effective and efficient neuro-evolution remains fairly ad-hoc and is masked behind problem-specific particulars. However, individuals of any species acquire more than one behavioural traits during their lifetime, some of which are evolved.

In this work we propose a more generic and systematic neuro-evolutionary framework which is not bounded by problem specifics and is applicable and adaptable to various learning and/or evolutionary tasks from different domains. It draws inspiration from the multi-disciplinary field of behavioural genetics (BG). Research in BG shows that genes and environment interact throughout development to shape differences in behaviour. The approach uses twin models to disentangle genetic and environmental influences on performance and the model captures the wide range of variability exhibited by population members as they are trained on and across five different tasks. Table 1 enlists the main steps involved in the method. Our approach enables a population of Artificial Neural Networks-ANNs to: *Optimise*- a population evolves or gets fitter at a given evolutionary task over generations at population level; *Adapt*- evolving populations are able to adapt to changes in the environment. These changes might be slow and subtle as in concept drift or they might occur abruptly as in concept shift; *Model interactions between learning and evolution* – thereby exemplifying how learning can shape and constrain evolution.

Findings

Our experiments explore the use of ANNs as computational models capable of sharing and retaining, and reusing knowledge by combining them with Genetic Algorithms. The framework was tested on five different cognition based tasks.

The experiments led to some interesting findings such as: applying selection on the individual's performance level in a quasi-regular task such as past tense acquisition results in the emergence of divergent behaviours depending on initial conditions – both genetic and environmental; once selection starts targeting a particular aspect of task domain, it starts behaving similar to Waddington's epigenetic landscape; and selection based on a stochastic method, such as roulette-wheel, when combined with sexual reproduction method for population generation has a limiting effect on final behavioural (or performance) levels achieved; further selection based on deterministic mechanism when coupled with sexual reproduction has more positive effects on final performance levels achieved, since it targets the domain general range of variation amongst chosen parameters. Thus, the parameters being targeted work well for all tasks, making transfer across heterogeneous tasks successful. Learning and evolution interact continuously and affect one another. The selection operator acting on the evolutionary task constrains learning abilities of the population of networks by targeting different computational parameters and their range of variations, and since selection is applied to the accuracy scores achieved by ANNs on evolutionary task after learning, these determine which kind of ANN progress forward in evolutionary scale.

1. Identify evolutionary and (if needed) learning task(s)
2. Simulate variations in genetic influences
3. Simulate variations in environmental influences
4. Generate initial population of ANN twins, $G(0)$ such that each individual is an ANN characterised by its own genetic and environmental influences. Set $i = 0$
5. REPEAT
   (a) *Train* each individual (ANN twin) using local search
   (b) Evaluate *Fitness* of each individual according to training performance. Also calculate heritability
   (c) *Select* parents from $G(i)$ based on their fitness on evolutionary task
   (d) Apply search operators to parents to produce offspring for $G(i+1)$
6. UNTIL, termination criterion is met

Table 1. High level description of the proposed framework .

Publications

Kohli, M., Magoulas, G.D., and Thomas, M.S.C. (2012): Hybrid Computational Model for Producing English Past Tense Verbs, In Proc the 13th Intern. Conf. Engineering Applications of Neural Networks (EANN), London, Springer CCIS 311 (pp. 315-324).

Kohli, M., Magoulas, G.D., Thomas, M.S.C. (2013): Transfer learning across heterogeneous tasks using behavioural genetic principles, In Proc. the 13th UK Workshop on Computational Intelligence (pp. 151-158).