A Population-Differential Method of Monitoring Success and Failure in Coevolution

Ari Bader-Natal and Jordan B. Pollack

DEMO Lab, Brandeis University, Waltham, MA 02454 USA
{ari,pollack}@cs.brandeis.edu

Abstract. Coevolutionary algorithms require no domain-specific measure of objective fitness, enabling these algorithms to be applied to domains for which no objective metric is known or for which known metrics are too expensive. But this flexibility comes at the expense of accountability. Past work on monitoring has focused on measuring *success*, but has ignored *failure*. This limitation is due to a common reliance on "best-of-generation" (BOG) based analysis [1], and we propose a population-differential analysis based on an alternate "all-of-generation" (AOG) framework that is not similarly limited.

Coevolutionary analysis based on *generation tables* was introduced by Cliff and Miller as *CIAO data* [2]. In dual-population coevolution, the table's rows are assigned to the first population's generations, and columns to the second population. Internal entries contain a best-vs-best evaluation of the intersecting generations. This BOG approach appears particularly problematic for two reasons. First, analysis varies depending on the definition of "best" (within a population), but this definition has become arbitrarily fixed on the *Last Elite Opponent* criterion [3], while alternate definitions are equally viable. The coevolutionary algorithm under examination may itself define "best" differently (e.g. Pareto coevolution as "on the Pareto front") in which case LEO is inappropriate. Second, while BOG-based analysis may give useful insight into algorithmic dynamics of successful individuals (i.e. the "best",) it provides little about the population as a whole (i.e. the "rest",) and is therefore blind to many failures.

For an "all-of-generation" alternative, rather than identifying the "best" member of both populations and recording the outcome of their interaction, AOG records the outcome of all interactions between every pairs of individuals from the two populations, respectively. In the data provided below, we implement this population-grained evaluation $PEval$ as an averaging of all individual evaluations (each of which is either *win*, *tie*, or *lose*, which is denoted numerically as 1, 0, and -1, respectively. Next we construct the *population-differential analysis* measure, based on the insight that the progression of candidate generations ought to perform better over time with respect to a fixed test generation (and vice versa) if successful. First we define a single distinction with the population comparators (between current generation i and oldest generation in memory, j). We then collect all available such comparisons at each (where o is the oldest known generation) with the candidate and test performance metrics.

Definition 1. $PC_{T_k}(C_i, C_j) = \begin{cases} 1, \text{if } a > b \\ 0, \text{if } a = b \\ -1, \text{if } a < b \end{cases}$ *and* $PC_{C_k}(T_i, T_j) = \begin{cases} 1, \text{if } c < d \\ 0, \text{if } c = d \\ -1, \text{if } c > d \end{cases}$

where $i > j$, C are candidate generations, T are test generations, $a = PEval(C_i, T_k)$, $b = PEval(C_j, T_k)$, $c = PEval(C_k, T_i)$ and $d = PEval(C_k, T_j)$. The *PC-Performance* graphs displayed are simply the average of this $CPerf$ and $TPerf$.

Definition 2. $CPerf_i = \dfrac{\sum_{T_k \in T} PC_{T_k}(C_i, C_o)}{|T|}$ *and* $TPerf_i = \dfrac{\sum_{C_k \in C} PC_{C_k}(T_i, T_o)}{|C|}$

As evident in the graphs below, the population-differential analysis is able to the closely mirror behavior of an exteral evaluation of performance.

Fig. 1. Fitness-proportional coevolution on *intransitive numbers game* domain [4]

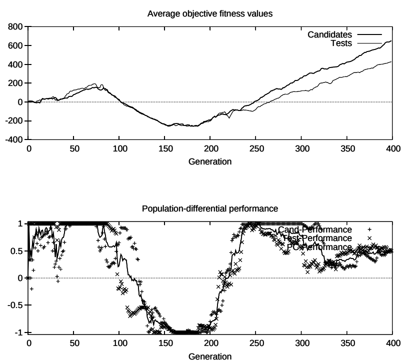
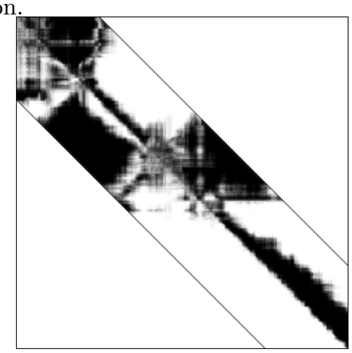


Fig. 2. AOG data from same simulation.



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