An analysis of ϵ-lexicase selection for large-scale many-objective optimization

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ABSTRACT

In this paper we adapt ϵ-lexicase selection, a parent selection strategy designed for genetic programming, to solve many-objective optimization problems. ϵ-lexicase selection has been shown to perform well in regression due to its use of full program semantics for conducting selection. A recent theoretical analysis showed that this selection strategy preserves individuals located near the boundaries of the Pareto front in semantic space. We hypothesize that this strategy of biasing search to extreme positions in objective space may be beneficial for many-objective optimization as the number of objectives increases. Here, we replace program semantics with objective fitness to define ϵ-lexicase selection for many-objective optimization. We then compare this method to multi-objective optimization methods from literature on problems ranging from 3 to 100 objectives. We find that ϵ-lexicase selection outperforms state-of-the-art optimization algorithms in terms of convergence to the Pareto front, spread of solutions, and CPU time for problems with more than 3 objectives.

CCS CONCEPTS

• **Theory of computation → Bio-inspired optimization**;

KEYWORDS

many-objective optimization, selection

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1 SUMMARY

The multi-objective optimization (MO) community is increasingly interested in algorithms that can scale to large numbers of objectives. Dealing with large numbers of objectives affects the search process [4, 5] and as a result, different types of algorithms perform well [2]. As research has progressed, studies have analyzed the ability of evolutionary multi-objective optimization (EMO) algorithms to find or appapproximate Pareto-optimal solution sets for problems with up to 6 [12], 50 [1], and more recently, 100 objectives [9].

At the same time that EMO research has moved to larger sets of objectives, the genetic algorithm (GA) and genetic programming (GP) communities have shown strong interest in the so-called "multi-objectivization" of single-objective problems [6]. In GP, the idea of restructuring search drivers around program semantics, defined as the outputs or behavior of a GP program, has gained traction [10]. Rather than aggregating performance across training instances, semantic methods can re-define the problem as a set of smaller objectives for driving search. One such method is lexicase selection [11], which uses program semantics to filter the population via randomized orders of training cases at each selection event. By doing so it is able to adapt selection pressure to subsets of training cases that are harder to solve.

A variant of lexicase selection [11] known as ϵ-lexicase selection was introduced to apply lexicase selection to continuous error spaces for symbolic regression [8]. A recent theoretical analysis considered ϵ-lexicase selection through a multi-objective lens [7]. It showed that ϵ-lexicase selects individuals located near boundaries of the Pareto set defined by the population's error vectors. In this sense, ϵ-lexicase selection demonstrated an instance of a multi-objective treatment of regression with promising results.

In this work[1], we evaluate the performance of ϵ-lexicase selection as a many-objective optimization algorithm, shown in Algorithm 1. Our experimental study consists of a comparison of ϵ-lexicase selection to two EMO algorithms: NSGA-II and HypE. We compared these methods on the scalable DTLZ problems [3] using 3 to 100 objectives. Performance was assessed using the convergence measure (CM) and the inverted generational distance (IGD), as recommended in [2, 9]. The results of this experiment are shown in terms of rankings in Figures 1 and 2. We also compared wall clock runtimes in Figure 3.

The results make a compelling case for ϵ-lexicase selection, especially for 5 to 100 objectives. In this range, it finds solution populations with better convergence measures than HypE or NSGA-II (p<0.01) with no significant difference from HypE in terms of IGD, a measure that takes into account spread along the Pareto front. In addition to these promising results, ϵ-lexicase selection finishes in significantly less time than the other methods for 25 to 100 objectives.

Future work should consider more adaptations of ϵ-lexicase selection to incorporate concepts from other EMOs. In a broader sense, the success of ϵ-lexicase selection suggests that it is useful to promote solutions near Pareto-set boundaries that perform well on randomized subsets of other objectives.

[1]Code: http://github.com/lacava/emo-lex

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Algorithm 1 : ϵ**-Lexicase Selection** applied to individuals $x \in \mathcal{N}$ with objective values $f_i(x)$, $f_i \in \mathcal{F}$.

Selection($\mathcal{N}$, $\mathcal{F}$) :
  $\mathcal{P} \leftarrow \emptyset$ ◊ parents
  for $f_i \in \mathcal{F}$: ◊ get ϵ for each f_i
    $\epsilon_i \leftarrow \lambda(\mathbf{f}_i)$
  do N **times**:
    $\mathcal{P} \leftarrow \mathcal{P} \cup$ GetParent($\mathcal{N}$, $\mathcal{F}$, ϵ) ◊ add selection to $\mathcal{P}$

GetParent($\mathcal{N}$, $\mathcal{F}$, ϵ) :
  $\mathcal{F}' \leftarrow \mathcal{F}$ ◊ objectives
  $\mathcal{S} \leftarrow \mathcal{N}$ ◊ selection pool
  while $|\mathcal{F}'| > 0$ **and** $|\mathcal{S}| > 1$:
    $f_i \leftarrow$ random choice from $\mathcal{F}'$ ◊ pick random f_i
    $f_i^* \leftarrow \min f_i(x)$ **for** $x \in \mathcal{S}$ ◊ best score on f_i in pool
    for $x \in \mathcal{S}$: ◊ filter pool
      if $f_i(x) > f_i^* + \epsilon_m$ **then**
        $\mathcal{S} \leftarrow \mathcal{S} \setminus \{x\}$
    $\mathcal{F}' \leftarrow \mathcal{F}' \setminus \{f_i\}$ ◊ remove f_i
  return random choice from $\mathcal{S}$

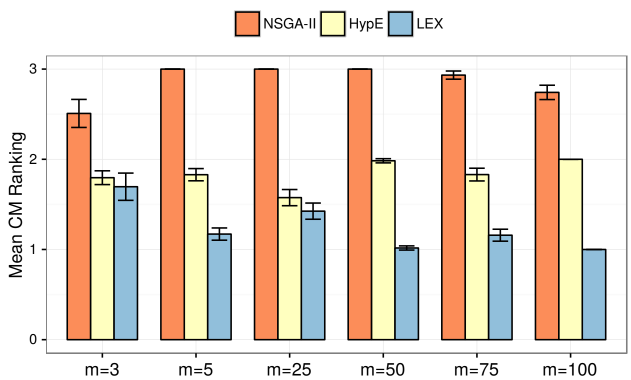

Figure 1: Average CM rankings of each algorithm as a function of number of objectives m**.**

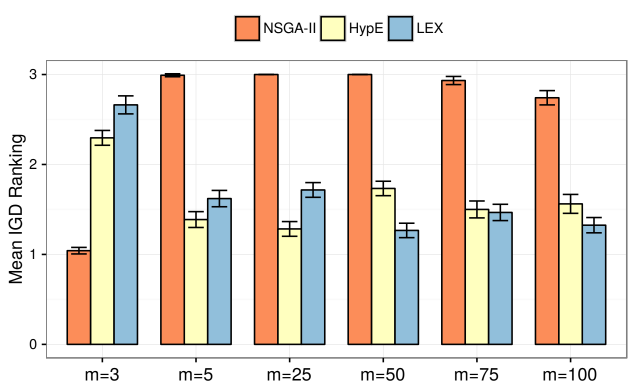

Figure 2: Average IGD rankings of each algorithm as a function of number of objectives m**.**

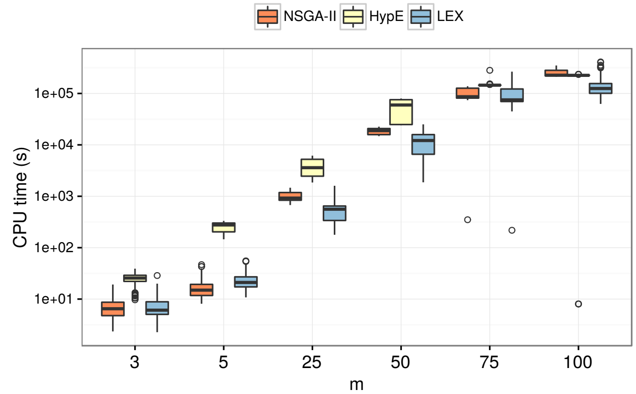

Figure 3: CPU time for each algorithm as a function of number of objectives m**.**

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