The Need to Transform Evolutionary Computation Research

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It is almost an article of faith that all evolutionary algorithms utilize random mutation. This level of randomness might have some justification in natural evolution in a dynamically changing environment. Or it may be necessary to use randomized operators when the evaluation function is a simulation and has no closed form. However when solving classic combinatorial optimization problems, random mutation is often unnecessary and unproductive.

Another recent trend is to characterize all evolutionary algorithms as "Black Box Optimizers" where nothing is known about the objective function. Unfortunately, "Black Box Optimizers" are subject to the restrictions of No Free Lunch theorems. More recent No Free Lunch proofs hold over finite and tractable sets of functions, making this a serious concern [8, 7].

Black box optimizers using random operators are doom to fail in any competition with more intelligent forms of search. Today, all competitive MAXSAT and Graph Coloring heuristic search methods deterministically compute the location of improving moves in constant time. For MAXSAT, this result has been known since 1992 [5]. Algorithms such as GSAT and Walksat do not enumerate bit flip neighborhoods, instead these algorithms can compute the location of improving moves [3]. Again this does **not** involve the enumeration of the bit flip neighborhood; instead the exact location of improving moves is determined analytically, on average in O(1) time. Under these conditions, mutation is hopelessly inefficient. New proofs show that these same results hold over all k-bounded pseudo Boolean functions [12, 9]. Just as all SAT problems can be reduced to a MAX-3SAT instance, all problems that have a bit representation can be transformed into a k-bounded pseudo Boolean function [1]. This raises an important challenge to all researchers working in evolutionary computation. Why does the field ignore these advances and continue to use random and blind black box operators?

In domains such as MAXSAT [6] and the Traveling Salesman Problem [4, 11] we can also prove that deterministic forms of recombination can offer new performance guarantees. Given q properly chosen crossover points, recombination is proven to return the best of 2^q possible offspring. If the parents are known to be local optima, all of the offspring are proven to also be locally optimal in largest hyperplane subspace that contains both parents [6].

Careful examination of another recent result, the optimization of one billion variable problems in the domain of cast scheduling, also reveals that no mutation is used. Instead a form of deterministic "block crossover" which is similar to partition crossover is used, as well as a deterministic form of "repair operators" instead of random mutation [2].

We argue that the only way for evolutionary algorithms to be competitive on many classic NP Hard optimization problems is to abandon "black box optimization" and adopt more intelligent search methods. The result is a form of Gray Box Optimization where knowledge about problem structure is actively and explicitly exploited [10]. A longer and more detailed discussion of deterministic operators can be found in the paper "Next Generation Genetic Algorithms" [13].

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