Chapter 3

NOVELTY SEARCH AND THE PROBLEM WITH OBJECTIVES

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Abstract  By synthesizing a growing body of work in search processes that are not driven by explicit objectives, this paper advances the hypothesis that there is a fundamental problem with the dominant paradigm of objective-based search in evolutionary computation and genetic programming: Most ambitious objectives do not illuminate a path to themselves. That is, the gradient of improvement induced by ambitious objectives tends to lead not to the objective itself but instead to dead-end local optima. Indirectly supporting this hypothesis, great discoveries often are not the result of objective-driven search. For example, the major inspiration for both evolutionary computation and genetic programming, natural evolution, innovates through an open-ended process that lacks a final objective. Similarly, large-scale cultural evolutionary processes, such as the evolution of technology, mathematics, and art, lack a unified fixed goal. In addition, direct evidence for this hypothesis is presented from a recently-introduced search algorithm called novelty search. Though ignorant of the ultimate objective of search, in many instances novelty search has counter-intuitively outperformed searching directly for the objective, including a wide variety of randomly-generated problems introduced in an experiment in this chapter. Thus a new understanding is beginning to emerge that suggests that searching for a fixed objective, which is the reigning paradigm in evolutionary computation and even machine learning as a whole, may ultimately limit what can be achieved. Yet the liberating implication of this hypothesis argued in this paper is that by embracing search processes that are not driven by explicit objectives, the breadth and depth of what is reachable through evolutionary methods such as genetic programming may be greatly expanded.

Keywords: Novelty search, objective-based search, non-objective search, deception, evolutionary computation
1. Introduction

Evolutionary computation (EC; De Jong, 2006; Holland, 1975) and genetic programming (GP; Koza, 1992) are algorithmic abstractions of natural evolution, inspired by nature’s prolific creativity and the astronomical complexity of its products. Supporting such abstractions, evolutionary algorithms (EAs) have achieved impressive results, sometimes exceeding the capabilities of human design (Koza et al., 2003; Spector et al., 1999). Yet the ambitious goal of evolving artifacts with complexity comparable to those crafted by natural evolution remains daunting.

An interesting question is what prevents EAs from evolving artifacts with a functional complexity of the magnitude seen in biological organisms. There are many possible answers, each pointing to potential faults in current EAs. For example, representation, selection, or the design of problem domains could each possibly be the paramount issue preventing higher achievement in EC, and there are researchers who investigate ways of improving each of these components (Pelikan et al., 2001; Stewart, 2001). This paper focuses on selection and argues that the currently dominant objective-based selection paradigm significantly limits the potential of EAs.

This handicap results from a well-known problem facing EAs called deception (Goldberg, 1987): Sometimes a mutation increases fitness but actually leads further from the objective. That is, the fitness function in EC is a heuristic and thus there is no guarantee that increasing fitness actually decreases the distance to the objective of the search. The fundamental problem is that the stepping stones that lead to the objective may not resemble the objective itself. For example, humans bear little resemblance to their flatworm ancestors. In the words of John Stuart Mill, it is a fallacy to assume that the “conditions of a phenomenon must, or at least probably will, resemble the phenomenon itself.” (Mill, 1846, p. 470). Yet this fallacy is the very foundation of typical fitness functions and thus ultimately limits their effectiveness.

In practice, researchers become accustomed to the fragility of fitness functions and learn certain rules of thumb that guide their efforts. One prominent such inductive rule is that the more ambitious the objective is, the less likely evolution will be able to solve it. This intuition, supported by experiments in this paper with increasingly difficult problems, highlights the critical problem undermining objective-based search: While we want to harness evolution to solve ambitious problems, the more ambitious the objective is, the less informative the gradient of the induced objective function will be. A provocative question is whether the quest for the objective itself sometimes precludes search from achieving anything remarkable. In other words, could ignoring the ultimate objective of search, or even searching entirely without an explicit objective, sometimes be a more viable approach to discovery?