Fitness Landscapes and Evolutionary Dynamics

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Abstract. This key note considers fitness landscapes and their use for understanding evolutionary dynamics in natural and artificial biological systems. Landscape paradigms are meanwhile ubiquitous in several branches of science. This introductory overview discusses concepts, issues and application with a main focus on evolutionary biology and evolutionary computation.

Introductory Overview

The origin of the complexity and beauty of living structures and processes is the product of evolutionary dynamics. The fundamental Darwinian ideas of evolution in connection with genetic coding offer an explanatory framework for these developments of biological systems. Main elements of this framework are an inheritable genetic coding that allows to pass on abilities and features of the living beings, their survival and reproduction success depending on these abilities and features and an uneven distribution of the success due to (possible changing) environmental conditions. In this context, one of the core questions is how the genetic make-up (roughly to the equated with genotype), the abilities and features (approximated as phenotype) and the survival and reproduction success (expressed as fitness) interrelated with each other. An attempt to capture these interrelations are fitness landscapes. In evolutionary biology they are used as a mathematical framework for understanding evolutionary dynamics. In engineering and computer science the Darwinian ideas of evolution found application in optimization and modelling tools using evolutionary computation techniques. Also here, for studying and analyzing these algorithms fitness landscapes are useful. So, the main focus is on finding and/or creating realistic fitness landscapes, on analyzing and visualization tools for fitness landscapes, on how fitness landscapes can help to understand working principles of evolutionary computation techniques, and on how these landscapes can be used to reflect complex evolutionary dynamics.

A (static) fitness landscape Λ_S can be expressed by [4, 13]

$$\Lambda_S = (\mathbb{X}, n, f), \tag{1}$$

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where $\mathbb{X}$ is a configuration space, $n(x)$ is a neighborhood structure that assigns to every $x \in \mathbb{X}$ a set of (more or less distant) neighbors, and $f(x) : \mathbb{X} \to \mathbb{R}$ is a fitness function that gives to every $x \in \mathbb{X}$ a proprietary quantity to be interpreted as a 'quality' information. In other words, the configuration space in connection with the neighborhood structure expresses a (possibly multi–dimensional) 'location', while the fitness is an orthogonal projection from location, defining an 'elevation' or 'height' and at the same time giving a location its most important property. Fitness is usually considered a single parameter but it seems perfectly possible to have a height measure with several dimensions.

The origin and character of configuration space, neighborhood structure and fitness function differ, naturally, in evolutionary biology and evolutionary computation. In evolutionary biology, the configuration space is made up by the genotypes of the biological system under study [17, 3]. The genotype characterizes the genetic make–up of a generic individual. It comprises of the sum (or union) of all genetically possible individuals and hence is the total genetic information. The neighborhood of a genotypical location is usually defined by the property of which genotypes can mutate from one to another [3]. Assigning fitness to each element of the genotypical space requires additional considerations. Up until recently, this question was answerable only purely theoretical and also requires to define an intermediate level between genotype and fitness, the phenotypical space. The reason for that is that it is complicated or even infeasible to assign a fitness value to the 'microscopic' genotype. Fitness, at least in any sensible biological sense, is connected to longevity and fertility and ultimately to reproduction success of a specific individual. Such a phenotypical individual can be thought of as an instance of the generic individual specified by a genotype. Hence, such a fitness landscape Λ_S is, strictly speaking, the product of a genotype–to–phenotype–to–fitness mapping and such landscapes have been the subject of much theoretical work on evolutionary dynamics [2, 15, 14, 8, 9]. However, some recent studies have shown that a direct experimental approach to construct fitness landscapes and analyze possible evolutionary pathways is possible [7, 5]. These results have led to a renewed interest in the framework of fitness landscapes as for the first time the question of the predictability of real evolutionary processes became addressable.

There is a fine but important conceptional difference in the approach to fitness landscapes in evolutionary biology and evolutionary computation. The main focus in evolutionary biology is to look for what fitness landscapes origin if we employ methods to extract its structure and topology from real biological data and what conclusions about the working and the outcome of the evolutionary process can be drawn from these landscapes. In evolutionary computation the main focus is on search for topological features in a landscape that is given by the optimization problem under study. This can be related to the question of how an evolutionary algorithm (an artificial model mimicking a simplified version of natural evolutionary processes) interacts with the landscape and what behavior and performance can be expected in the search.

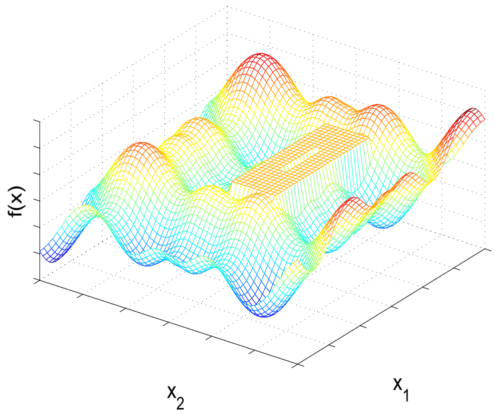

Fig. 1 Static fitness landscape in $\mathbb{R}^2$ as mountainous region with peaks, valleys, ridges and plateaus

In evolutionary computation, therefore, the configuration space is made up by the search space obtained from encoding all possible solutions of the optimization problem. The neighborhood structure is a consequence of the search space and hence the objects to be optimized over, but also of the genetic operators the evolutionary search employs [4]. If the search space is metric (as for instance if the search space elements are real or integer numbers, and the genetic operators act on these numbers), then the neighborhood structure is inherent by the ordering of numbers. If the search space is not metric (or can have several different kinds of metrics), the neighborhood structure needs to be defined additionally. Examples are binary coding, where the neighborhood structure can be a Hamming distance of different length, or tree representation where the neighbors of a branch differ by a (smaller or larger) variation in a subtree.

As discussed so far, fitness landscapes in both evolutionary biology and evolutionary computation have the same base and are an attempt to answer similar or highly related questions. If, as a special case, we consider the configuration space as two–dimensional and the neighborhood structure continuously metric, we end up with the fitness landscape metaphor frequently depicted: that of a mountainous region with peaks, valleys, ridges and plateaus, see Fig. 1. It appears almost a little surprising that such a rather naive picture has meaning in branches of sciences as illustrious as physics, biology and informatics. Interestingly, landscape paradigms are closely related to conceptualization of behavior that is usually related to complexity [10, 1]. The main motivation to employ a landscape approach is that it offers a framework for a computational treatment. This treatment becomes geometrically interpretable in a meaningful way for the aforementioned simple two–dimensional case, but there is a multitude of ways to employ landscape measures or visualization methods that are applicable for any given configuration space dimension [8, 9, 16, 6].

The fitness landscape approach presented here has been applied to different kinds of problems in both evolutionary biology and evolutionary computation, and yields understanding of evolutionary dynamics. I think that the recent progresses and findings might be the beginnings for further developments that promise to address even more fundamental questions about the working and the outcome of evolutionary processes.

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