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ON EVOLUTIONARY AND REVOLUTIONARY ALGORITHMS

Abstract

Evolutionary algorithms allow solving ubiquitous optimization problems by applying methodologies that are metaphor of biological evolution. The optimal solution is represented by a code that represents the best fit among a population of individuals. This optimal representation is obtained through the application of basic stochastic operators borrowed from genetics (e.g. mutation, crossing-over, bitflipping …). To overcome the time limitations of evolution, cultural algorithms introduce the "belief space" representing prior knowledge. To prevent stereotyped behavior within a belief space, implying definitely an involution, a competition procedure on both sub-population of individuals and the related belief spaces is generated. These kinds of procedures are referred to "revolutionary algorithms". Through a captivating notion of politics, they permit the exploration of unexpected regions of the search space.

Introduction

Evolution is a fundamental tenet of modern science. Although it derives from biology, it is also a unifying principle of diverse research fields among which economics and financial sciences. In a computational framework, the global set of arguments on which neo-Darwinian paradigm rests on translates into a limited number of statistical rules and processes that operate on databases of populations.

These rules are normally referred to as mutation, generation, combination, selection, competition, and reproduction, which are also terms borrowed from biology. The mentioned processes ensure life in a universe that has been shown to increase entropy at a global level (positively entropic). Evolution is the result of the stochastic interaction of these basic processes on populations giving collectively raise to generations more and more fitted to the environment, which is also dynamically changing on different time-scales.

Evolution is a dynamic and integrated process that can be simulated on computers and devices to help solving difficult optimization problems. The optimization of nonlinear dynamic problems, of the type typically met in both engineering and financial sciences, is widespread: for example, a minimization (maximization) multivariate search problem can be cast into an optimization one; also, the data compression process can be reinterpreted as an optimization problem with constraints.

The solution of an optimization problem is normally found iteratively and based on the landscape at hand it can be computationally expensive and time-consuming. Finally, there is no guarantee to find the true optimal solution of the search.

Evolutionary strategies and genetic algorithms are the two typical computational approaches to find evolved optimal solution to the optimization problems. In practical problems, given a task, the search procedure starts with a population of contending trial solutions; new possible solutions are generated through stochastic processes based on the selected operators and the various contenders are evaluated through a fitness (i.e., objective) measure. This measure is commonly adopted as an error function whose resulting value ultimately determine the selection of next generation trial solutions: the best fitted data survive and are maintained as parents for the subsequent set of offspring. Different alternative procedures are available in the literature to generate data structures that can optimally represent solutions. Evolutionary algorithms encompass all of those techniques in a unique framework.

To find acceptable solutions of a complex problem, a procedure of search for a minimum is carried out: typically, the optimization in a dynamic scenario implies to find a balance between computational costs and re-initialization. In a static problem, the search of the minimum of a function is carried out by the gradient descent. The rapidity of the convergence is ruled by some parameters that in the machine learning approach are normally known as learning rate and momentum. Successive iteration steps starting from an initial guess choice permit to reach the minimum. The minimum is thus dependent on the initial choice that also defines a specific region of the cost function. For a nonlinear mapping, the consequence is that normally a local minimum is obtained that can be sub-optimally good for the problem at hand (Figure 1). Obviously, it certainly exists a better solution for our problem. A bad choice of the momentum parameter implies instead jumps around the true (possibly local) minimum that can be interpreted as a stereotyped behavior.

In many cases, the local minimum reached is not responding to the application needs and the search for an alternative minimum is carried out by escaping the valley corresponding to the previous minimum. The jump in a different valley is typically obtained through the addition of a stochastic term to the function to be optimized or through a quantic tunneling process (Figure 2). In a deterministic framework, this can be done by initializing parallel search procedures in multiple sub-regions of the same cost function. Of course, the efficiency of the global process is decreased and strongly depends on the number of sub-regions involved. It is also related to the computational power of the computers involved.

Unfortunately, many problems of practical interest are dynamic; for example, the optimization of a portfolio is done while the markers are yet trading. In those cases, the optimal solution is changing while we are searching for it and the global scenario is volatile.The change of landscape obliges each time to restart the optimization procedure: a side effect of this approach is evidently the loss of information on the previous search.

A good way to face these problems is yielded by the so-called "cultural algorithms". They allow a sort of a priori knowledge to be embedded in the search procedure that facilitates the definition of a good minimum. Revolutionary algorithms can be seen as a smart evolution of cultural algorithms.

Evolutionary Algorithms

The evolutionary computation (EC) concept has been originally proposed in [1], as a novel paradigm to solve difficult optimization problems. Some related ideas have been presented in [2], whereas in [3] the evolutionary approach has been proposed even as a way to increase industrial production!. However, it was the application at the learning process of artificial neural networks that paved the way to more grounded studies on evolutionary and genetic algorithms [4]. This was also made possible because of the availability of supercomputers. The major advantages of EC are the flexibility and versatility to match the task specifications, the robustness of performance, and the possibility it yields to make a global search into a defined space. Indeed, the problem solving abilities of EC can be seen as adaptable optimization strategies mainly based on heuristics. EC can be used to solve real-world problems where the cost function and the related constraints cannot be expressed analytically, for example in simulation problems. In these problems, a set of optimal free parameters must be determined by minimizing a cost (objective) function. Various aspects prevent to finding the optimal solution[5]: 1) existence of strong nonlinearities; 2) large dimensionality of the search space (e.g., big data); 3) presence of many local minima and restrictions on the search space in the form of constraints; 4) noisy background; 5) non-stationary objective functions due to dynamic adaptation to the environment. EC can practically provide an effective approach to the above-mentioned characteristic problems.

EC have the capacity to mimic the process of natural evolution through an iterated two-step procedure that implies: 1) generation of populations from individuals; 2) evaluation of new genetic information and selection of the best individuals. Each individual is both affected by the whole population and by the environmental conditions. Over the course of the procedure, the best-fitted individuals prevail within a population, thus giving rise to well adapted generations. The optimization problem solution involves the description of the individuals and of the related search space, the definition of suitable operators to modify the individuals, and the design of a proper selection mechanism.

As a difference with standard genetic algorithms, where the free parameters subject to optimization are binary strings modified by suitable operators (i.e., mutation, crossing-over, flipping, etc.); in EC, the mutation is carried out by a random change to each parameter through adding to them a normally distributed random value with zero meaning and unity standard deviation. In both circumstances, the search space is visited in the course of the search procedure by possible re-initialization.

The main limitation of EC is time. This is related to the very concept of biological evolution. The Italian poet Eugenio Montale, indeed, wrote:

"L'evoluzione biologica
Ha un passo così lento che a quel metro
La lumaca è un fulmine"
("Biological evolution
Proceeds so slowly that at its pace
The snail is lightning.")

Cultural Algorithms

The Cultural Algorithm, CA [6] is an extension of EC and it is basically a Meta-Evolutionary algorithm. It is similar to other meta-extensions of EC like the Memetic Algorithm [10]. It is inspired by the concept of culture as knowledge or beliefs of society's members. Culture is formed and evolves by interacting with the environment through positive or negative feedback cycles. During the course of evolution, individuals of a population accumulate knowledge that is conveyed to other individuals in the population. Collectively, all of the accumulated information generates a "knowledge base" (or, a fuzzy databank of rules) that can be exploited by individuals of the population. Positive feedback mechanisms occur where cultural knowledge reflects regions of good fitness: in this case,information is passed to next generations, possibly adapted to match society's changes. The cultural knowledge base is also useful to warn against regions of potential hazard.In the context of an optimization procedure, the objective of the knowledge-based CA is to increase the speed of convergence of an EC search technique. The algorithm operates in two steps: 1) at the population level CA is an evolutionary search, where individuals representing candidate solutions share common characteristics that are represented into a cost function in the problem domain; 2) information acquired by generations is stored in a knowledge or beliefspace, which is accessible to the current generation. A suitable communication protocol is defined in order to permit interaction between the population components and the belief space.

The knowledge-base (Belief Space) can be used to store the best candidate solution found and any information about the areas of the search space that are expected to yield good candidate solutions. This "cultural" knowledge is accessed by the population-based EC search, thus influencing subsequent generations. The fitness function constrains the transfer of knowledge from the population to the belief system (write access) and manages how the belief space influences the individuals. To extend the EC notion of survival of the fittest individuals, only a selected sub-part of the population can update the belief space.

CA can be extended to multi-population approaches [7]. If various parallel populations have been initialized, the best solutions of the respective belief spaces can be exchanged. This process may imply the migration of individuals between belief spaces.

An interesting step forward to CA is the inclusion of the concept of negotiations between belief spaces. The negotiations of possible behaviors are carried out through the instrument of politics. In a human-like context, the presence of politics induces ideology. Individuals of populations may adhere to ideology for different reasons. At a certain time, a specific culture is hegemonic in the sense that it is able to provide optimal solutions. In a dynamically changing environment, typical of trading markets, alternative "ideologies" can develop and gradually substitute the present belief space. In politics, this can be interpreted as a sort of "revolution".

Revolutionary Algorithms

The basic concept of "revolutionary algorithms"(RAs) is the presence of various different sub-populations that do not share the same belief space, i.e. they have different cultures. According to this principle, they extend the EC algorithms by evolving the trace of CA.

Revolutionary Algorithms [8] emulate the political process of change of hegemony. From the technical viewpoint, RA is an extension of CAs with multiple sub-populations each possessing their own belief space (Figure 3). The sub-populations are able to exchange information with the belief space: the individuals with high fitness may write the rules, and, in turn, the belief space dictates the ways the individuals reproduce. The process is started randomly; then the individuals adhere to a belief space. The selected belief space is more likely the more successful, i.e. the one that gives more significant improvement in the search procedure. Initially, the optimization process is fast; however, at later stages, any improvement is costly. In this case, it is possible that an alternative belief space can influence and attract the population originally belonging to the original belief space. The change of belief space can be understood in the framework of the search procedure by thinking to a jump to a different zone of the search space. A different patch of rules in the fuzzy logic approach covers this new zone. In the metaphor of the search for a minimum as a solution of an optimization problem, RA is merely a data-driven change of perspective: the detection of changes in the data, merely dynamic, creates interest for different parts of the search space (i.e., a different belief space satisfying the "dissidents" of the old hegemonic culture).

In finance, the change of paradigm implied by RA is ruled by the market. In the search for a minimum, it is favored by the onset of "involution". This is easily represented by a descent procedure where we jump around the minimum without never reaching it. This sort of stereotyped behavior suggests forming new generations based on a different belief space. From a thermodynamic perspective, the involution happens in a space's region where the entropy decreases. In the course of dynamics, the growth of entropy related to irreversibility is guaranteed in the global universe (see I. Prigogine works); however, in local parts it is possible to meet decreasing entropy (this has been shown to be related to reduction of complexity [9], here represented by "involute" behavior).

Conclusions

This paper presented synthetically how the concepts of evolution, involution, and revolution can be implemented in a computational framework. Starting from the concept of evolutionary algorithms, some extensions have been considered where the search for the optimal solution can become dynamic and follow the changes of rules determined by the environment. The concept of politics influences the development of revolutionary algorithms: in an optimization procedure, this means to investigate local regions not well represented in the original space of EC and not well described by the belief space of CAs.

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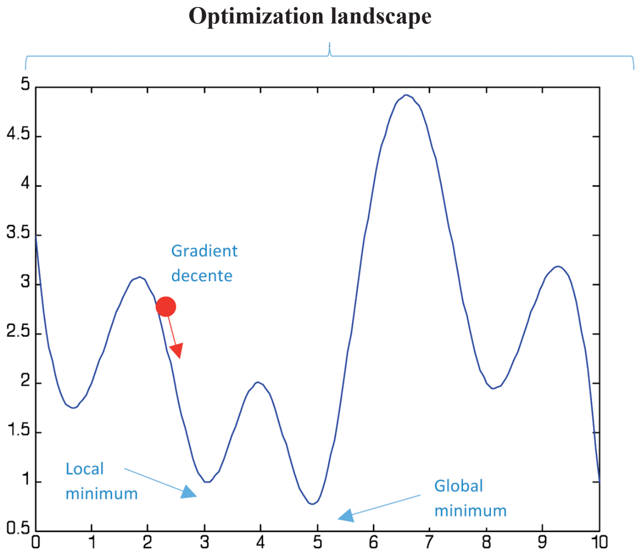

Figure 1 – Search for a minimum in a nonlinear (multimodal) search space.
To reach the global minimum is impossible starting from an erroneous initial state.

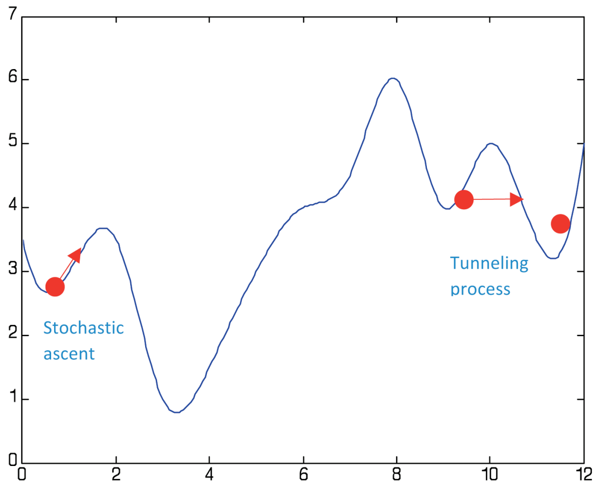

Figure 2 – The Evolutionary Computation (EC) algorithms allow to jump in different region spaces through stochastic ascent or the quantic tunneling process.

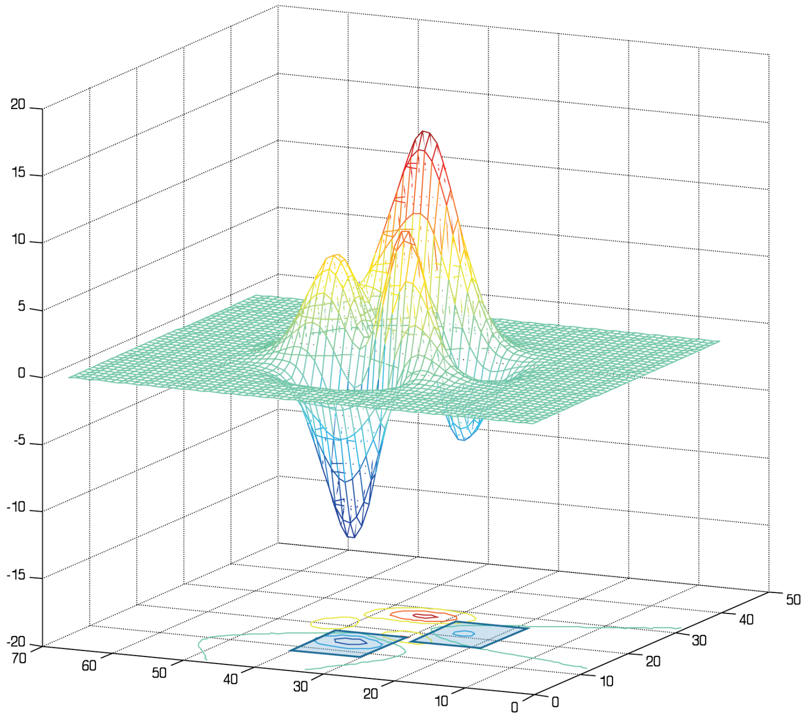

Figure 3– The Revolutionary Algorithms allows to explore different regions spaces related to different belief models or fuzzy patches of rules.