

Introduction: Genetic Algorithms in Visual Art and Music

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Source: *Leonardo*, 2002, Vol. 35, No. 2 (2002), pp. 175-184

Published by: The MIT Press

Stable URL: <https://www.jstor.org/stable/1577199>

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INTRODUCTION

Genetic Algorithms
in Visual Art and Music

L*eonardo* has a long tradition of publishing work at the mutual frontier of art and science. We are pleased to present in the pages of *Leonardo* a special project that demonstrates the application of ideas from science (evolutionary biology), technology (computing) and art (both visual art and music). The topic of this special section is the application of genetic algorithms and related heuristics to visual art and music. These texts were first presented at the Genetic Algorithms in Visual Art and Music workshop at the 2000 Genetic and Evolutionary Computation Conference (GECCO) in Las Vegas [1]. The texts will be published in two installments in *Leonardo*—the first installment here and the second set of papers in Vol. 35, No. 4 (August 2002).

Genetic algorithms, invented by John Holland in the 1970s [2], are part of a heuristic method that abstracts the processes found in biological evolution and simulates them on a computer. However, instead of being used to simulate real biology, genetic algorithms are used to solve problems in many non-biological domains.

A typical use of genetic algorithms is in optimization, where we want to search some virtual space for the individual (in this case, either an image or a piece of sound/music) that scores highest in some selected measure. The genetic algorithm first generates a random set of individuals drawn from the set of possible individuals that could exist (this set is known as the *search space*). In the context of an artistic system this could be the generation of random sounds or images. Typically, these individuals are represented as binary strings, which facili-

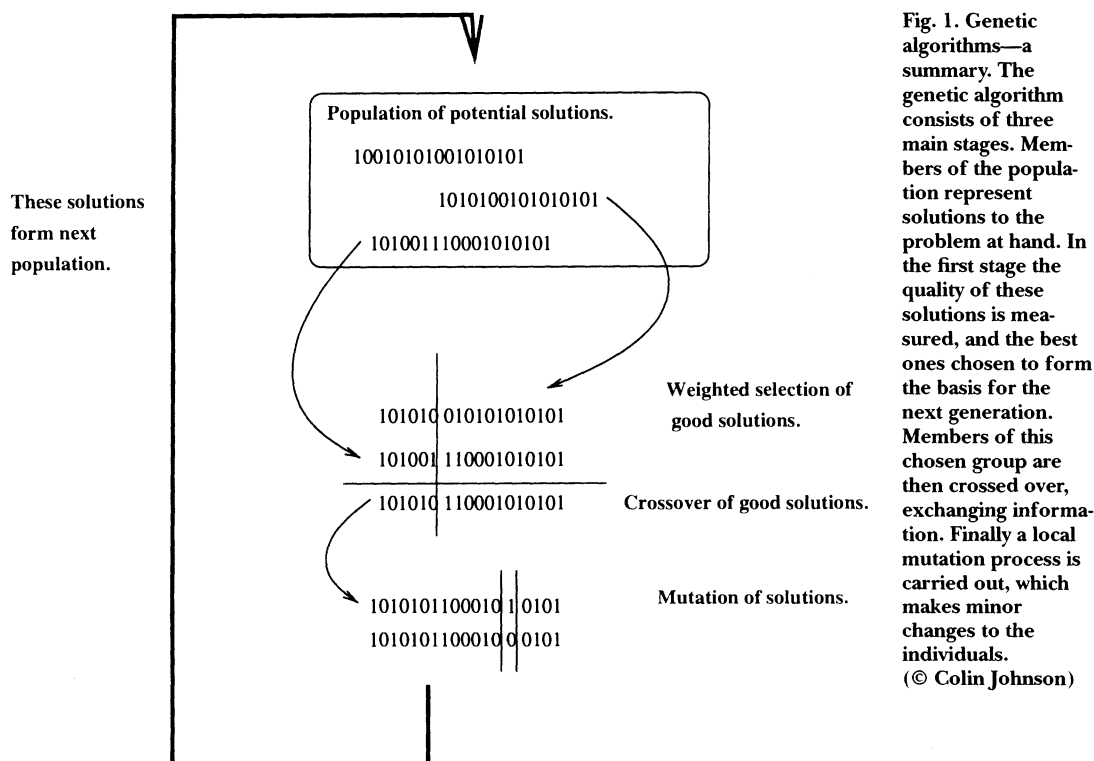


Fig. 1. Genetic algorithms—a summary. The genetic algorithm consists of three main stages. Members of the population represent solutions to the problem at hand. In the first stage the quality of these solutions is measured, and the best ones chosen to form the basis for the next generation. Members of this chosen group are then crossed over, exchanging information. Finally a local mutation process is carried out, which makes minor changes to the individuals. (© Colin Johnson)

tates the application of the crossover and mutation operators described below. After the best individuals in the population are selected (either by a human, a computer or a combination of the two), they exchange information with other individuals (a process known as *crossover*) and small changes are then made in the individuals (i.e. they undergo *mutation*), resulting in a new population. This process is repeated (see Fig. 1) either until a satisfactory result is found or until the population reaches a state where the individuals are all very similar to one another. In this latter state there is no variation left for evolution to work on—it is said that that population has *converged*.

Procedures such as this have proven to be a powerful way to search many different kinds of search space, with many real-world applications, such as timetabling, scheduling, operations research problems, design of control systems, computer-aided design of architectural structures, parameter setting in neural networks, and data mining [3]. A number of other techniques, such as cellular automata [4], artificial life [5] and autonomous agents [6], have similar “flavors” and have also been used in artistic and musical areas.

A number of researchers have investigated the use of genetic algorithms in artistic domains. The Genetic Algorithms in Visual Art and Music workshop was held to review the state of the art in this area. This workshop included presentations of papers, general discussions of the topics presented and demonstrations of art and music created using these systems, including a live performance by John Biles and his GenJam system. The articles presented here are extended versions of the papers presented at the workshop.

In this introduction, we begin by providing some general background to this area and a review of prior work on these topics. One of the aims of the workshop was to consider whether there are any general principles or major open questions that underlie this field of research. Some of the papers discuss such topics individually, and some general questions are gathered together in the final section of this article.

We would like to thank the participants and authors for their contributions to the workshop and for revising their papers for this special section with utmost efficiency.

OVERVIEW

Many people have dreamed of a computer with human features. The idea of how such a “human computer” would manifest varies, depending on one’s conception of humanity or on the feature to be highlighted. The idea of intelligence as a differentiating characteristic, which gave rise to the term “Artificial Intelligence,” was one of the most common ideas in the old dream of creating artificial humanity. Other researchers have put forward notions of creativity, learning or adaptation capacity in general.

The papers presented in this project analyze works that try to realize, using computers, one of the most thrilling tasks that human beings are capable of: art. Art possesses features that make it a fascinating area of inquiry for exploring the “human” capacities of a computational system. Art also has features that present challenges when using traditional computational techniques to produce it:

- The first characteristic of art is its dynamism. Artistic and aesthetic trends evolve through time from a community point of view, coexisting at a given point in time among different societies and within the same society.
- A related interesting feature of art is its social character—art is inconceivable without a set of interrelated individuals. We can see how, even within a given set of aesthetics or concrete artistic styles, a work of art is evaluated differently according to the critic and the time.
- Art is closely linked to humanity’s instinctive and irrational side. In many cases, we learn by Socratic learning or environmental immersion, even while the learning has not been totally comprehended or formalized.

The desire to use computation for building artistic systems can be traced back to Ada Lovelace, who dreamt 150 years ago of the creation of a computer with musical capabilities. From that moment, artificial artistic systems have been studied using numerous computational techniques, including expert systems, artificial neural networks and statistical and stochastic methods.

There have also been attempts, throughout the history of music, to formalize the act of musical creation. At different times in the history of Western music, proposed compositional formalisms have claimed that musical works could be created as a result of applying certain rules to some given initial material. This idea survives in some present-day musical styles and musical computation projects that deal with composition [7]. On the other hand, we find systems based on the use of a simple algorithm on a numeric or symbolic series. In this case, the series may have a great variety of origins and may contain non-musical material. These systems are called “mathematical” or “fractal” systems. Generally speaking, in such systems the sensations produced by the music or art arise from characteristics of the system that are generated by the author of the system rather than being automatically generated within the system itself.

We can also speak of the perspective that considers music as a language. From this perspective, composition consists of the creation of a message that transmits a certain content, following the rules of culture, cultural style and personal style. This idea, which is more complex and complete than the previous one, allows for the introduction of cultural (i.e. group) and particular (i.e. individual) factors into the process, bringing the concept of analysis into the composition. Therefore, while the previous conceptualizations were purely generative (the results springing from a set of rules bearing no relation to the environment), in this case an analytic component allows the introduction of common aesthetic rules into the compositional system.

Much of the research carried out in recent years suggests the creation of artificial artistic systems using evolutionary techniques. Evolutionary computation is inspired by nature, taking features of the evolution process and applying them to the computational field. These techniques, which started with Holland’s work in 1975, offer a variety of solutions to a given problem. The most highly adapted ones give rise to new generations of solutions through crossover, mutation and selection genetic operators.

Evolutionary computation has a number of distinctive features. On the one hand, this technique has a high degree of adaptation capacity, due to its origin; in fact, few things are as adaptable as nature. This adaptation capacity is possible thanks to the use of control or feedback structures, where future change takes into account how similar changes have affected similar systems in the past. Further, the social character of such a method is obvious, both in the way in which structures in such systems emerge from interactions (occurring in parallel) throughout various parts of the system, and in the importance of communication (understood as exchange), especially in areas such as artificial life. Another remarkable feature is the possibility of incorporating various forms of musical knowledge, not necessarily just formal rules. Thus, since the abstraction of artistic information is not necessary, the information is not biased.

Evolutionary composition results in dynamic models whose behavior is not totally defined by the model’s creator. We do not yet thoroughly “understand” art; however, if we had only techniques that were limited to our understanding, the creation of art would be out of reach right now. Such evolutionary computational systems have proved to be very accurate in fields that require a certain degree of creativity [8], such as those related to visual and musical art, as will be discussed later.

We may distinguish two roles in any system of artistic creation: the creator (or author) and the critic (or audience). In the works presented in this project, the researchers serve in the role of the critic, while the creator’s role is played by an evolutionary computational system. A number of articles have been written providing deeper analyses of some of these implementations in the field of music [9].

This paper gives a perspective on the various arms of research into artificial artistic systems using evolutionary techniques. We have classified the papers based on the “critic” element of the different compositions and will analyze four types of works: interactive systems, systems based on examples, rule-based systems, and autonomous systems (Fig. 2). Finally, we propose the integration of these various works in a common framework, where different approaches can compete and/or collaborate to create global compositions adaptable to different types of music and art, thus incorporating the features of these different techniques.

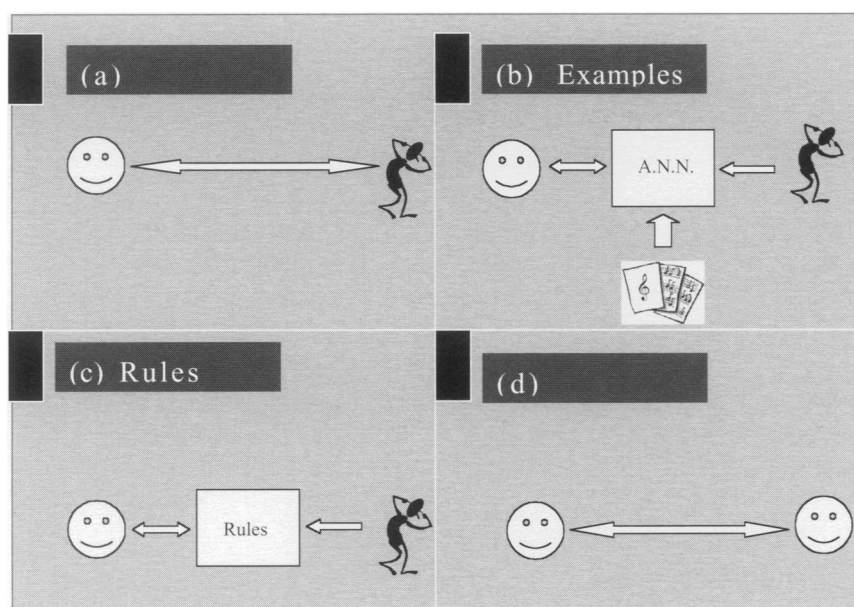


Fig. 2. Different ways of interacting with the evolutionary composer oriented to musical works. (a) The user acts as critic of the system's compositions. (b) The user introduces a series of examples in order to train the artificial neural network, which will work as a critic of the evolutionary system's compositions. (c) The user defines a set of rules used to evaluate the system's compositions. (d) Composer and critic are part of the system and they evolve simultaneously. (© Juan Jesús Romero Cardalda)

Interactive Systems

In interactive systems, the critic is a human being who makes an aesthetic evaluation of each composition in the system and thus conducts its evolution. The system takes these evaluations into account for the creation of the next set of compositions. The user's conducting role can be played by a single person or by a group; in the latter case, the members of the group assess the cybernetic composer's works of art simultaneously.

These systems, in their simplest form, pose the problem of excessive time cost (or "bottle-neck") due to human participation [10]. This problem may also tire users, who have to evaluate a great number of musical examples. Although these systems can be said to have a high degree of subjectivity, the direct role of the user allows for the evolution of works with the right aesthetic conception for the individual or group interacting with the system.

In the musical field, we find works of art made by interactive systems that use variations on existing melodies [11], new melodies [12], jazz improvisations [13], rhythmical textures [14], scores based on material provided by the user [15] and newly generated sounds [16].

In the visual domain, we should highlight a number of notable pieces: first, the work of Karl Sims with his "Creatures" and the evolution of complex simulated structures, textures and motions [17]; and, second, the work of William Latham, who generates live three-dimensional forms in his "organic art" [18]. There are also systems related to architecture [19], two-dimensional pictures [20] and systems incorporating design and exploration of visual spaces [21].

Systems Based on Examples

The possibility of registering a user's tastes within a subsystem of a system for artistic or musical creation has been suggested in some instances, with a twofold intention. The first purpose would be that of improving the system's learning rate and using the current generation of artistic works to conduct the direction of evolution. The second purpose would be solving the problems of interactive systems related to their slow speed and subjectivity. User preferences are often integrated into an artistic or musical system by means of an artificial neural network trained by exposure to artistic pieces (an artificial neural network is a type of computer system that tries to simulate the behavior of the natural neuron and can learn from samples). These pieces can be examples of a particular artistic style or author, or they may stem from an interactive system. In the musical world, we may find examples of such pieces in the rhythmic domain [22], in jazz (such as music inspired by Charlie Parker's songs [23]) and in Western four-part harmony compositions [24]. In the visual domain, we find examples in two-dimensional pictures [25].

Rule-Based Systems

In rule-based systems, the critic is built from a set of rules that conducts the system. This set of rules is built by the system's author from his/her musical knowledge or artistic studies. In the musical domain, most of the works are related to harmonization [26]. There are also systems that make jazz solos [27], one that makes minimalist music [28] and another with two critics—a set of rules and the user [29].

Autonomous Systems

A radical change in the separation between system and user occurs in systems that have their own autonomous aesthetics. In this case, artistic works evolve following their own path, which may have nothing to do with human aesthetics. Such systems are usually regarded as models of social evolution.

Autonomous musical systems include two types of works: works in which some elements work as evaluators and others work as composition creators, while both evolve simultaneously [30], and works that compose melodies and generate sounds using artificial-life techniques [31].

Conclusions

The state of the art described here reflects the thriving moment that the field of genetic algorithms is going through. There is a promising diversity, quantity and quality of works. One problem in this field is the high degree of dispersion of these works, coupled with the fact that there are few conferences on this specific area, making the spread of field work difficult. However, this situation is beginning to change, thanks to conferences such as the Musical Creativity symposium, which was part of AISB '99 (Artificial Intelligence and the Simulation of Behaviour, 1999 symposium), and our workshop, which was part of GECCO 2000. Such events will also enable closer collaboration among researchers.

OUTSTANDING QUESTIONS

One of the aims of our workshop was not just to allow people to talk about and hear about developments in this exciting area, but also to try to identify important questions spanning this whole area of research. Much work has been done in this field, and we feel that there is a sufficient body of work from which to draw together some common experiences and consolidate the major questions in this area. Here, we will discuss some of these questions.

One difficulty inherent in musical applications of genetic algorithms that is not found in visual applications is the large amount of time required to listen to the various members of the population. This makes assigning a score to members of the population time-consuming. Trying to resolve this problem is an important question for the application of these techniques. The problem is less significant for visual applications, as the user can examine more than one picture at once and can compare two images directly by looking from one to the other. Nonetheless, comparing and rating many visual items over a period of time can be tiring.

Fitness Bottlenecks

One approach that shows promise in the area of fitness bottlenecks is to integrate the scoring system into the context of an activity. This idea is demonstrated in a number of the articles in this section. A musical example is John Biles' GenJam system, in which the human performer plays a passage, followed by the computer, which plays while being rated by either the human performer or the audience. This involves the listener(s) in an experience that is much closer to ordinary music-making than a process where the listener has to rate each member of a population in a separate process. Another example of these ideas is given in the paper by Moroni et al. Duncan Rowland and Frank Biocca describe in their article a work that uses a similar process to embed the evolution of visual objects in a particular context—the work places their evolving objects in the context of a virtual sculpture park. A future direction for such models would be to explore fitness creation in an indirect way—for example, a sculpture park that created new sculptures based on those the user has paid the most visual attention to in a virtual environment.

Another approach that may have promise, one not explored in any of the articles here, would be to pre-process the population so that the user could get an idea in advance of the scope of what can be generated by the algorithm. It may be possible to do this using a non-interactive genetic algorithm or another search technique. In this case, we would construct the fitness automatically by giving a high score to those elements of the population that are most different from the previous population members. Clearly defining “difference” would be the biggest challenge here. The aim of this would be to present the user of the system with a tour around the different kinds of structures that could be found in the search space. Reconstructing this tour would enable the user to see a sampling of the different types of object that the search space could produce.

There are other potential approaches. One of these could involve using a machine learning mechanism to monitor user choices and attempt to “second guess” the user. This could involve a learning method such as a neural network. However, one study has shown that it is difficult to train a neural network to learn some features of music [32], due perhaps to the complexity of the interplay between individual musical gestures and the different meanings of those gestures in different contexts. Alternatively, this could involve some form of analysis of the chosen objects and an attempt to identify features common to many of the chosen objects.

Yet another alternative would involve starting with objects of low complexity, evolving a low-complexity object, then evolving more complex features later. This would circumvent the problem of evolving detailed features that only work in context, only to have those detailed features vanish when we change the large-scale structure of the object. Reducing the load (or apparent load) on the user without reducing the quality of the exploration is a major area of exploration, one that research has only just begun to touch.

Agents

Another area with much potential for future research has been identified in John Biles’ paper [33]. His system evolves an agent that then creates pieces of music. This contrasts with many of the other systems described in this paper, which create music or art by applying evolutionary algorithms directly to musical or artistic objects. This idea of evolving agents to carry out the task is also explored in the paper by Alejandro Pazos et al. [34]. The use of agents allows us to use such systems in different contexts. For example, we can train an agent in private, then use it in a live public performance, as is done with GenJam. We can also imagine a new kind of collaborative musical activity where, instead of improvising directly with other musicians, we create agents that represent us in a group music-making activity. This has similarities to computer games such as *Creatures*, where the player creates autonomous agents and releases them into an environment, rather than sitting directly at the controls of the agent. Another agent-like approach is the use of ideas from cellular automata and artificial life. These ideas are explored in the paper by Eduardo Reck Miranda [35].

Comparisons with Traditional Applications of Genetic Algorithms

Other interesting questions arise: to what extent are these musical and artistic applications of genetic algorithms similar to traditional genetic algorithms, what are the differences, and how might we design genetic algorithms for artistic application areas? This remains a largely open field of enquiry. Initially we can consider how the exploratory nature of many of these algorithms makes them different from the traditional genetic algorithm, in which the desired ideal outcome can be specified at the beginning. Do these new applications require more diversity in the population than the traditional genetic algorithm? Do we need more mutation to ensure the creation of new areas to explore—or new operators entirely? Do we need to encode members of the population differently for applications where the genetic algorithm is being used as an exploratory tool rather than as an optimization tool?

We can also consider the extent to which the generation of fitness by having a “human in the loop” makes a difference. This situation makes a number of changes to the algorithm; for

example, it will no longer be certain that, when an individual appears twice in a population, that individual is assigned the same fitness. Indeed, there is evidence that the fitness declines as users become bored with the same individual [36]. How fitness is assigned, how users assign fitness relative to other individuals and to absolutes, and how we can influence user behavior so that they make best use of the algorithms are interesting questions.

Coherence of Populations

Another question that ties in with the mathematical theory of genetic algorithms is the extent to which we can take individuals and “drag and drop” them between different populations. Tatsuo Unemi, in his article, brings up the possibility of taking one picture (i.e. individual) and dropping it into another population. This is used in his application to add diversity to a population that has undergone premature convergence, that is, where the population has settled on a small number of solutions with little variation across the population. Such a technique can potentially be used to create more subtle effects, such as putting certain images aside and then introducing them into another population to steer that population towards images more like the introduced images. Colin Johnson discusses this question further in his article [37].

Combining Sound and Images

Unemi’s use of both sound and images in his software brings up another issue. At present, his software evolves images only, and the sound is pre-composed. However, this opens up the possibility of evolving both sound and images through a joint process. One possibility would be to use evolutionary algorithms for sound and images, using separate populations but with a common fitness rating given to sound and image played together. A more interesting possibility is to create both from a common source. One way in which this could be done would be to generate the images and sound from the same set of parameters, using different algorithms. At the crudest level, this would be little more than lights flashing on and off in time with the music, but it has potential for the creation of a more sophisticated system. Perhaps more interesting would be to generate the image and the sound not just using the same parameters, but using the same algorithm. This raises the question of whether our aesthetic feelings about a piece of algorithmic art are generated by the algorithm or by the particular result of the algorithm’s realization. Are we likely to see some kind of “harmony” between two realizations of the same algorithm through different media? Is our reaction entirely reliant on the way the algorithm is realized? Is it a mixture of the two? This brings up questions that have been raised in the past [38], when fractal pictures were first generated and musicians attempted to create musical analogs of these images by incorporating the underlying algorithms. These new ways of exploring these spaces have the potential to provide new tools for the investigation of such phenomena.

Analysis of Music and Art

So far we have discussed the use of genetic algorithms in the creation of music and visual art. However, in articles such as that by Francine Federman [39], we read of systems that could provide the foundation not just for creation, but also for analysis. Federman describes a system that is able to anticipate the next note in a melody. Such a system could be used to extract common patterns from different kinds of music and to classify these patterns. Data from such classification of the differences between different kinds of music could be extracted to create a data-mining–driven style of musical analysis. There are also potential applications in the analysis of style, for example in the attribution of authorship or in studying which musicians have influenced others.

CONCLUSIONS

Genetic algorithms present a powerful means of exploring complex systems in a focused way. The papers in this section illustrate how these ideas can be applied across a range of artistic

and musical areas, and outline the many challenges ahead in developing these ideas further. We hope that *Leonardo* readers will enjoy the papers in this section.

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GLOSSARY

cellular automata—computational processes based around a set of locations (the "cells"), each of which can contain one of a set of states. Typically the cells are arranged so that there is some geometrical relationship between them, for example by placing them in a line or on a grid. The process consists of changing the states in the cells over a number of discrete time-steps, with the state in a particular cell taking a new value depending on its current value and the values of its neighbors. These processes can produce intricate patterns from simple sets of rules specifying this update process.

convergence—the state when the population in a genetic algorithm has settled into a small number of values, with little variation between members of the population.

crossover—the exchange of information between two objects in the population of a genetic algorithm. This facilitates the bringing together in one object components of two objects, each of which contributes positively to a solution.

fitness—the fitness of a particular object in the population of a genetic algorithm is a measure of its quality, interestingness or relevance. In traditional applications of genetic algorithms, the fitness is given by a fixed fitness function that takes objects from the population and assigns a fitness score to them according to their success at solving the problem at hand. In many of the applications discussed in this paper the fitness is made by the user of the system using aesthetic criteria.

genetic algorithm—a computational process that is an abstraction of the evolutionary process found in the natural biological world. The aim of a genetic algorithm is to explore some large parameterized space of objects. Initially a random selection of these objects is made; this collection is known as the *population*. This population is then changed over the course of a number of time-steps. At each time-step a number of processes are carried out. First, a fitness rating is given to each object in the population; this specifies how likely it is that that individual will be used in forming the next population. Second, new objects are created by a two-stage process: first, high-fitness individuals are crossed over with each other, and then a small mutation is made to some of them. This new collection of objects then forms the new population, and the process repeats.

mutation—the process whereby a small change is made to an object in the population of a genetic algorithm. This facilitates the trial of minor variations on good solutions and ensures that new material is constantly being brought into the population.

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