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Evolutionary Computation

Abstract

In the rapidly advancing field of Artificial Intelligence, its subfield of Evolutionary Computation has emerged as a versatile and powerful paradigm. This paper is a comprehensive overview of Evolutionary Computation: highlighting its fundamental principles, diverse variants, and historical development. Primarily utilized to solve optimization problems and optimize those that already exist, Evolutionary Computation takes inspiration from evolution's mechanism of natural selection to provide solutions. This inspiration leverages principles like selection, variation, and retention of superior solutions to iteratively improve upon existing approaches.

Evolutionary Computation's modern-day applications in multiple scientific fields will be explored as well as unveiling both its robust capabilities and limitations. This paper emphasizes Evolutionary Computation's enduring relevance and potential as an adaptable tool for solving complex optimization problems. Its adaptive nature and iterative improvement distinguish EC as a versatile tool applicable across diverse domains, from engineering to biology, addressing a wide range of optimization challenges with its evolution-inspired methodology. By bridging the gap between nature-inspired methods and modern practical applications, Evolutionary Computation continues to inspire researchers and engineers to push the boundaries of artificial intelligence.

Introduction

Nature has been the inspiration for many human-made technologies. One notable example is George de Mastral discovering the Burdock's seed packet's ability to cling to him and his dog due to its tiny hook design. He later took inspiration from this design and developed Velcro. Evolution, the process that drove nature to achieve this tiny hook design, is the inspiration behind Evolutionary Computation. Thus, Evolutionary Computation is composed of two critical elements: a variation system and a selection system. Similar to how the seed design was not nature's first iteration, Evolutionary Computation utilizes 'generations' of mix-matching solutions to approach the most optimal solution for a problem.

History

As exemplified, Evolutionary Computation is the study of the foundations and the applications of computational techniques based on the principles of natural evolution [4]. Evolutionary-inspired approaches for optimization were first documented in the 1950s [1]. For example, George E. P. Box published an article in the Journal of the Royal Statistical Society in 1957 titled 'Evolutionary Operation: A Method for Increasing Industrial Productivity' [1]. In this article, he discusses a method to increase the productivity of manufacturing that is essentially a 'more powerful and concentrated form of the naturally occurring evolutionary process' [1]. Numerous other articles on Evolutionary Computation approaches were also published in the 1950s, encompassing evolutionary strategies by Ingo Rechenberg and Hans-Paul Schwefel, genetic algorithms by John

Henry Holland, and evolutionary programming by Lawrence J Fogel, which triggered further study [4].

Functional Insight

As previously stated, Evolutionary Computation consists of two systems: a variation and a selection. The variation system states that given a problem, the problem plays the role of an environment that sustains a population of individuals, each representing a possible solution to the problem. These individuals are heuristically generated by the variation system. The degree of adaptation of each individual to its environment is the measure of viability as a solution to the overall problem. This viability is measured by a predefined quality criterion, an adequacy measure known as the fitness function [4]. This evaluation happens at every step, or generation of the process. Next is the selection system, where a subset of individuals are selected per their fitness (i.e. how viable they are as solutions). Similar to evolution in nature, evolutionary algorithms will gradually produce more optimal solutions to the problem [4]. In other words, this process is guided by the Darwinian principle of survival of the fittest. The fittest (being the most viable solutions) are used to produce potentially more viable solutions over time. This results in effective solutions that were not explicitly 'engineered' and 'designed' by humans.

Constraints

Evolutionary Computation, like any other process, has its constraints. Risto Miikkulainen, a professor of Computer Science at The University of Texas at Austin, spoke on how there are events in nature that we do not fully understand with our current knowledge of biology, hence making it difficult to represent similar events in Evolutionary Computation. One such example is the biological process of a singular cell transforming into a multi-cell organism. These 'major transition' events have not been replicated using Evolutionary Computation, emphasizing its current limitations. Keith Downing, a professor of Computer Science at NTNU[1], explained in his 2013 TedTalk [5], that the process of requiring selection to determine the most appropriate solutions is rather unpredictable and can produce confusing solutions that require further investigation. Those solutions may require an understanding of dynamical systems theory[2] and/or information theory[3].

Variations of Evolutionary Computation

Evolutionary Computation differs from the standard engineering problem-solving approach, where efficiency and safety can be mathematically induced before the experiment. Trust in the solution comes from a complete understanding of the process and the result. However, as mentioned previously, the solutions provided by Evolutionary Computation can be unpredictable and difficult to understand [5]. However, if the selection is constrained, you take away from the 'creativity' aspect of the process that nature has to offer, which can lead to inaccurate or ineffective results. In an interview with Risto Miikkulainen [2], he states that scientists more often experiment with modifications of Evolutionary Computation that use the latter approach. One such modification involves refining the variation system through a statistical framework. By leveraging data and correlations, this framework identifies changes or mutations with the highest likelihood of positive impact. This is in line with all other processes used in Machine Learning and Artificial Intelligence.

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[2] Dynamic Systems Theory (DST) is a framework used to understand how systems change and develop over time.

[3] Information theory is the mathematical study of the quantification, storage, and communication of information.

Conclusion

Echoing Miikkulainen's insight, 'The main power of artificial intelligence is not in modeling what we already know, but in creating solutions that are new' [3], Evolutionary Computation stands as a testament to this principle. By harnessing the mechanisms of natural selection and genetic inheritance, it propels the creation of innovative and efficient solutions. In the past twenty years, Evolutionary Computation has leaned towards using statistics to sway selection as a way to more accurately and quickly develop solutions. This step appears suitable, but from my perspective, it might limit the range of potential solutions that could be generated. To me, Evolutionary Computation represents a unique, fascinating, and powerful paradigm—one that is ultimately constrained by our understanding of biology. In my view, the more we embrace and advance Evolutionary Computation, the more we uncover about ourselves and the natural world, shedding light on their origins and complexities.

References

[1] Box, George E. P. "Evolutionary Operation: A Method for Increasing Industrial Productivity." *Applied Statistics*, vol. 6, no. 2, Wiley-Blackwell, June 1957, p. 81. https://doi.org/10.2307/2985505.

[2] Lex Clips. "How Evolutionary Computation Works | Risto Miikkulainen and Lex Fridman." *YouTube*, 22 Apr. 2021, www.youtube.com/watch?v=KW4kPqnJcTQ.

[3] Miikkulainen, R. Creative AI Through Evolutionary Computation: Principles and Examples. *SN COMPUT. SCI.* 2, 163 (2021). https://doi.org/10.1007/s42979-021-00540-9

[4] Peña-Reyes, Carlos Andrés, and Moshe Sipper. "Evolutionary Computation in Medicine: An Overview." *Artificial Intelligence in Medicine*, vol. 19, no. 1, Elsevier BV, May 2000, pp. 1–23. https://doi.org/10.1016/s0933-3657(99)00047-0.

[5] TEDx Talks. "Evolutionary Computation: Keith Downing at TEDxTrondheim." *YouTube*, 4 Nov. 2013, www.youtube.com/watch?v=D3zUmfDd79s.