

# Evolutionary Approach to Machine Learning and Deep Neural Networks

Hitoshi Iba

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Neuro-Evolution and Gene Regulatory  
Networks

Hitoshi Iba  
The University of Tokyo  
Tokyo  
Japan

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# Preface

Around 1990, I learned about GP (Genetic Programming) and developed interest in this area shortly after learning about GAs (Genetic Algorithms). At that time, the term GP was not yet established, and the concept was denoted by terms such as structural GA and tree representation GA [1–3]. Since I had been researching AI so far, I presumed that the only goal of GA was optimization (my opinion has changed since), and I considered GA to be somewhat unsatisfactory. Consequently, as I assumed that GA could not be used for handling knowledge representation, programs, concept trees, and similar notions, I attempted to extend it. At exactly the same time, when I presented my research to Dr. Philip D. Laird from NASA, who was a Visiting Researcher at the Electrotechnical Laboratory. Dr. Laird is a researcher in machine learning and is renowned for his book *Learning from Good and Bad Data* [4]. He introduced me to the research of Prof. John Koza of Stanford University. I still remember the excitement I felt while reading the technical reports [5] written by Koza over the new year holidays. These reports were later compiled in a massive volume that exceeded 800 pages [6]. Afterward, I stayed at Stanford University in his laboratory and had a wonderful research life there.

Recently, an increasing number of researchers and students are specializing in only GA and GP (and fields centered on them). Also, in comparison with the time when AI and GA/GP were created, there are fewer and fewer researchers with unique personalities. Although this is not in anyway disappointing, it cannot be understood unless one has experienced the turmoil and the emotions associated with the establishment of a new field. I expect such pleasant nervousness and excitement to be maintained in this academic society as well, setting the path for the development of a healthy community. This is one of my motivations in writing this book.

The characteristics of EA (evolutionary algorithm) can be summarized as follows:

- **Parallelism:** A large number of individuals can be searched simultaneously as a group. This is suited to advanced parallel application and can fully utilize computer power.
- **Searchability:** EA does not presume a deep knowledge of the search space (calculation of differentiability, gradient, etc.)
- **Diversity:** As there are a wide variety of individuals within the group, it excels in adapting to environments with dynamic changing problems and noise, and the solutions obtained have a high level of robustness.

We can introduce such promising biological knowledge, e.g., symbiosis, coevolution, and habitat isolation, into the calculation mechanism in EA.

For this purpose, this book provides theoretical and practical knowledge about a methodology for EA-based search strategy with the integration of several machine learning and deep learning techniques, e.g., memetic concepts, neural networks, Gröbner bases, belief networks, and affinity propagation. The development of such tools contributes to better optimizing methodologies.

The concepts presented in this book aim to promote and facilitate the effective research in EA approaches in both theory and practice. However, the contents of the book would be valuable to different classes of readers because it covers interdisciplinary research topics that encompass machine learning methodologies, deep neural networks, neuroevolution, and gene regulatory networks. EA practitioners will find this book useful for studying evolutionary search and optimization techniques in combination with deep learning and machine learning frameworks.

In addition, while still undeveloped and unrefined, some of the research examples shown in this book include contents worthy of scrutiny and publication in a thesis. However, it is not my wish to preemptively dismiss interesting and challenging attempts in actively developing fields such as AI and EA, so this book actively introduces such research topics. I sincerely hope readers further develop these research examples to achieve fruitful results.

In parallel to EA and GP, which constitute rather general search methods, researchers in this field must be equally versatile and must look beyond their own fields of specialization to learn about new topics in order to pursue new models and applications. As long as research is conducted with this attitude, it will be possible to “sustain the dream” for both a scientific community and individual researchers. I hope that this book will help readers make such an academic venture in EA and AI fields.

Tokyo, Japan  
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Hitoshi Iba

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