Machine Learning and Optimization Algorithms Based on the Concept of Fitness Relativity

ヴァスコンセロス ヴァルガス, ダニロ

https://doi.org/10.15017/1785427

出版情報：九州大学, 2016, 博士（学術）, 課程博士
バージョン：

（別紙様式２）

氏　　名　：ダニロ　ヴァスコンセロス　ヴァルガス

論文題名　：Machine Learning and Optimization Algorithms Based on the Concept of Fitness Relativity
（適応度相対性概念に基づく機械学習および最適化アルゴリズムに関する研究）

区　　分　：甲

論　文　内　容　の　要　旨

This thesis introduces the idea of fitness relativity where the goodness of a candidate solution is not absolute. To show the importance of the concept, here novel optimization and machine learning algorithms using the concept are shown to surpass other state-of-the-art algorithms.

Fitness relativity is applied to optimization by first creating other fitnesses (objective functions) that aid search. Next, a population (table of candidate solutions) is created for each fitness. In this manner, the fitness of a solution is relative to its subpopulation. Two algorithms based on the new paradigm are developed. Tests shown that this division of objectives into populations tamed the conflict that happens when many objectives are used inside one population.

The concept of fitness relativity is also applied to machine learning, by dividing the input space, creating many smaller problems. Notice that the fitness for each smaller problem differs with each other as well as with the original one. The benefit of this division of input space is that the created smaller problems are easier to solve than the original one. Here, algorithms implementing the concept create a new paradigm of machine learning algorithms by automatically dividing the input space at the same time that they solve the created smaller problems. Results shown that such algorithms can adapt well to problem changes, cope with noisy and solve a wide range of complex problems from classification to reinforcement learning.

Moreover, to develop the main algorithms, various other secondary novel ideas and algorithms were developed such as:

- MONA, the first multi-objective algorithm based solely on novelty;
- Novelty Map, a novel unsupervised learning algorithm based on novelty;
- General Subpopulation Framework, a framework that can integrate any number of optimization algorithms as well as aid the design of structured ones;
- Two algorithms using the subpopulation framework;
- NOTC, the first multi-objective team-individual based reinforcement learning algorithm

An outline of the thesis is presented as follows:

Chapter 1 introduces the work, while Fitness relativity will be explained in details in Chapter 2. In Chapter 3 and 4 a brief introduction to respectively optimization and evolutionary algorithms are present.

One of the main works of this thesis is presented in Chapter 5, where a new subpopulation based framework generalizing structured evolutionary algorithms is defined and fitness relativity is applied to optimization in two algorithms based on this framework. Chapter 5 finishes the work on optimization and from there on I will introduce a bit of machine learning background before applying fitness relativity to machine learning. Learning is essentially the junction of optimization, models and an objective function related to minimizing the learning error. Therefore, first of all I define and present some models (representations) in Chapter 6. In Chapter 7 learning is defined followed up by Chapters 8 and 9 reviewing respectively the background in unsupervised learning and reinforcement learning, both subareas of machine learning. Evolutionary machine learning is briefly reviewed in Chapter 10 while Chapter 11 demonstrate how fitness relativity will be used in the context of machine learning. In Chapter 12 a new paradigm of evolutionary machine learning called Self-Organizing Classifiers (SOC) is proposed, where solutions are developed at the same time that the problem is being divided into smaller ones. A new unsupervised learning method based on novelty is presented in Chapter 13, which is used as part of the new version of SOC based on novelty, called Novelty Organizing Classifiers (Chapters 14 and 15). The conclusions are discussed in Chapter 16.