Chapter XVIII
Heterogeneous Learning Using Genetic Algorithms

Thomas Vallée
LEN, Nantes University, France

ABSTRACT

The goal of this chapter is twofold. First, assuming that all agents belong to a genetic population, the evolution of inflation learning will be studied using a heterogeneous genetic learning process. Second, by using real-floating-point coding and different genetic operators, the quality of the learning tools and their possible impact on the learning process will be examined.

INTRODUCTION

A quick analysis of the most recent literature in economics shows a tremendous increase in the number of articles using *genetic algorithms (GAs)*. This tendency can be observed in nearly all areas of economics, from econometrics to finance (see Vallée & Yildizoǧu, 2004, for a panorama of GAs' applications in economics). Nevertheless, although GAs are always learning algorithms, the motivations for using GAs in economics may be divided into two categories. First, GAs may be used as a *simple* numerical learning tool. That is, GAs will be used in order to find numerical values for nonlinear models of growth (Dorsey & Mayer, 1995; Beaumont & Bradshaw, 1995), optimal parameters values of some nonlinear regressions (Pan, Chen, Khang, & Zhang, 1995), best functions of regression (Szpiro, 1997), and best stock exchange estimators (Pereira, 2000). Second, and related to this chapter, GAs may be used as a metaphor of individual/social learning process in order to study, for example, the equilibrium convergence in some dynamic macroeconomics models (Arifovic, 1996, 2001; Dawid, 1999), how cooperation may emerge in prisoner dilemma game (Axelrod, 1987; Yao & Darwen, 2000), or the individual R&D strategies of firms (Yýldýzoǧlu, 2002).

This chapter belongs to the second use of GAs. It will show how one can use a genetic algorithm in order to simulate and understand a learning process in a particular economic model. In this chapter, the economic model we use is a standard Keneysian monetary game as described in many economics textbooks (e.g., Mankiw, 2004). We chose this particular model for two reasons. First, its simplicity. Second, it generated a huge literature dealing with time inconsistency (Kydland & Prescott, 1977; Vallée, Deissenberg, & Başar, 1999), credibility (Cukierman & Meltzer, 1986; Drazen & Masson, 1993), reputation (Barro & Gordon, 1983; Backus & Driffill, 1985), and central bank independence (McCallum, 1997; Blinder, 1998; Driffil & Rotondi, (2005).

This extensive literature on credibility suggests that an optimal response to cheating behavior requires punishment. Here cheating is understood as a discrepancy between an agent's announced and implemented strategies. The analysis is often applied to understand, for example, the unemployment-inflation tradeoff dilemma.

Obviously, if an economic agent wants to punish another one, there is a need to find an efficient punishment strategy. This is characterized by minimizing both the likelihood that future cheating behavior will occur and the eventual costs to the punisher. In many scenarios such an optimal punishment strategy may initially be unknown. As a consequence, the punisher will have to invest resources in order to learn it.

In this chapter, such a learning process will be modeled using genetic algorithms (GAs). In the proposed framework, each agent is understood to be a member of the genetic population. Although the learning process in GAs is an adaptive one, each member may not learn in the same way. Indeed, some agents may implement strategies that are incompatible with the optimal learning process. Thus, as indicated by Dawid (1996), GAs appear to be a suitable tool to model such a heterogeneous learning process. Nonetheless, effectively using such a GA requires a full understanding of its mechanism.

The behavior of GAs is strongly determined by the balance between exploiting what already works best and exploring possibilities that might eventually evolve into something even better (Herrera, 2000). Riechmann (1999, 2001) showed that three different learning schemes are contained in GAs: these correspond to learning by imitation, by communication, and by experiment. Whereas the former takes place as a follow-the-leader process, learning by communication happens when economic agents meet and exchange information, while the ability of at least one agent to innovate is crucial for learning by experiment.

In this chapter it is contended that the foregoing interpretations of learning are not sufficient. More specifically, genetic learning should be analyzed as an information treatment process built on two components. First, there is a need to generate and transmit a given quantity of information. Such a process can be realized by experiment, imitation, or improving the quality of communication. Second, this information must be appropriately used. In other words, the agents must have the capacity to evaluate such information in order to properly respond by an appropriate change of strategy. Of course, there are key issues concerning the quality of the foregoing processes, as well as to the optimal quantity of information to be exchanged. Thus, a poor assimilation of available information can hamper a learning process. Similarly, unsuitable, insufficient, or excessive information may interfere with the quality of a learning process.

The goal of this chapter is twofold. First, assuming that all agents belong to a genetic population, the evolution of inflation learning

Related Content

Particle Swarm Optimization Algorithm as a Tool for Profile Optimization
Goran Klepac (2015). *International Journal of Natural Computing Research (pp. 1-23).*
www.irma-international.org/article/particle-swarm-optimization-algorithm-as-a-tool-for-profile-optimization/164539

Anti-Synchronization of Pan and Lorenz-Lu-Liu-Cai Chaotic Systems by Active Nonlinear Control
Ayub Khanand Ram Pravesh Prasad (2012). *International Journal of Artificial Life Research (pp. 15-25).*
www.irma-international.org/article/anti-synchronization-pan-lorenz-liu/74333

Neuromorphic Computing: Transforming Edge and IoT Technologies
Devendra G. Pandey, Yogesh Kumar Sharmaand Nimish Kumar (2025). *Revolutionizing AI with Brain-Inspired Technology: Neuromorphic Computing (pp. 411-428).*
www.irma-international.org/chapter/neuromorphic-computing/362960

Agent-Based Modelnig with Boundedly Rational Agents
E. Ebenhoh (2007). *Handbook of Research on Nature-Inspired Computing for Economics and Management (pp. 225-245).*
www.irma-international.org/chapter/agent-based-modelnig-boundedly-rational/21132

Neighbor Topology for Dynamic Plane Coverage in Swarm Leading Control
Keitaro Naruseand Tatsuya Sato (2012). *International Journal of Artificial Life Research (pp. 59-75).*
www.irma-international.org/article/neighbor-topology-dynamic-plane-coverage/65076