The COMPARISON BETWEEN SOCIAL LEARNING AND INDIVIDUAL LEARNING: THE APPROACH BASED ON GENETIC PROGRAMMING

Chia-Hsuan Yeh, Dept. Dept. of Info. Manage., I-Shou Univ. Taiwan*
Shu-Heng Chen, Dept. of Economics., National Chengchi Univ. Taiwan

EXTENDED ABSTRACT

Economic simulations have been widely employed in the study of economics. The learning behavior of economic agents is also modeled by the computational framework. Different learning algorithms are used to *simulate* different style of learning behavior. In the literature, they can be classified into social learning and individual learning. In the social learning, traders learn from other traders' experience, while they learn from their own experience in the individual learning. The implications between social learning and individual learning have been stressed. However, what's more important is that the simulation result is not only influenced by *how we learn*, but also *what we can learn*. In other words, both of the learning styles and potential knowledge space contribute to the outcome. In terms of the techniques of evolutionary computation, the potential knowledge space is related to the representation. Therefore, how we represent the knowledge is one of the most important steps in the economic simulations. In Lucas (1986),

> In general terms, we view or model an individual as a collection of decision rules (rules that dictate the action to be taken in given situations) and a set of preferences used to evaluate the outcomes arising from particular situation-action combinations. These decision rules are continuously under review and revision; new decision rules are tried and tested against experience, and rules that produce desirable outcomes supplant those that do not. (pp. 217)

From the viewpoint of representation, if a decision rule can *hopefully* be written and implemented as a computer program, and since every program in terms of its input-output structure can be understood as a function. Then, based on the language of LISP program, every function can be represented as a LISP S-Expression, and hence a parse tree. This representation of decision rule is exactly what genetic programming does.

In the past few years, genetic algorithms (GAs) and genetic programming (GP) are

---

* *Corresponding author address:* Chia-Hsuan Yeh, Department of Information Management, I-Shou University, Kaohsiung County, Taiwan 84008, E-mail: spockyeh@ms38.hinet.net
Research support from NSC grants No. 89-2415-H-214-002 is gratefully acknowledged.

frequently used to model economic agents. There are two ways to implement GAs and GP, that is, single-population GAs (GP) and multi-population GAs (GP) which are distinguished from social learning and individual learning. In Vriend (2000), he pointed out their difference and consequences based on the framework of genetic algorithms. However, according to the traditional implementation of GAs, the pre-specified domain knowledge is required, which makes the result more parochial. In this paper, multi-population GP is employed. The topic used to investigate the influence of social learning and individual learning is the *artificial stock market*.

The basic framework of the artificial stock market considered in this paper is the standard asset pricing model employed in Grossman and Stiglitz (1980). The dynamics of market is determined by an interaction of many heterogeneous agents. In this market, there are two assets available for traders to invest. One is the riskless interest-bearing asset called *money*, and the other is the risky asset known as the *stock*. At each period, each of them has to make a decision about how many shares of stock he should hold based on his forecast about the future (the sum of price and dividends in the next period) in order to maximize the one-period expected utility. Their forecasts are formed by genetic programming. The control parameters of genetic programming are shown in Table 1.

At the evaluation date t, each trader has to make a decision. Should he change his mind (the strategy used in the previous period)? This psychological activity is modeled by two probabilities which describe the intensity of peer pressure and self-realization respectively. If the trader decides to change idea, then he will go to the business school (in the social learning) or think about it (in the individual learning) to get useful strategies. Once he get a new idea, he will compare the new idea with his old one used in the previous period. If the new idea outperforms his old idea, he will adopt the new one. Otherwise, he will go to the business school or think about it once again until either he succeeds or he fails for a pre-specified times.

In order to understand the difference between social learning and individual learning more precisely based on the representation of GP, we consider three different scenarios, Market A, B and C. The markets B and C are distinguished by the different number of ideas in each trader's mind. Market A is the case of social learning which is the same one in Yeh and Chen (2000). In this paper, the influence of the number of ideas for each trader is discussed. In principle, the traders are more adaptive when they have more ideas in mind. Therefore, they have more chances to discover the patterns of price dynamics, so their survivability is also higher. However, they may cause the market more complicated beyond control. Their survivability is then reduced. Which one is the most possible outcome needed to be studied.

TABLE 1 : Parameters of the Stock Market

The Stock Market	
Shares of the stock (H)	100
Initial money supply (M_1)	100
Interest rate (r)	0.1
Stochastic process (D_t)	Uniform distribution, U(5.01,14.99)
Parameters of Genetic Programming	
Function set	{+,-, ×,%,Sin,Cos,Exp,Rlog,Abs,$\sqrt{}$}
Terminal set	$\{P_t, P_{t-1}, \ldots, P_{t-10}, P_t+D_t, \ldots, P_{t-10}+D_{t-10}\}$
Selection scheme	Tournament selection
Probability of creating a tree by reproduction	0.10
Probability of creating a tree by immigration	0.20
Probability of creating a tree by crossover	0.35
Probability of creating a tree by mutation	0.35
Probability of mutation	0.3
Probability of leaf selection under crossover	0.5
Mutation scheme	Tree mutation
Replacement scheme	(1+1) Strategy
Maximum depth of tree	17
Maximum number in the domain of Exp	1700
Number of generations	4000
Traders	
Number of traders (N)	100
Number of ideas for each trader	1 (A, Social Learning), 10 (B), 25 (C)
Degree of RRA (λ)	0.5
Criterion of fitness (Traders)	Increments in wealth (Income)

Based on the experimental design described above, the difference between social learning and individual learning is then investigated. In this paper, we focus on

- their chance in discovering the fundamental price,
- the market efficiency,
- their chance in generating exotic behavior.

Keywords: Social Learning, Individual Learning, Genetic Programming, Artificial Stock Market

Reference

Chen, S.-H., and C.-H. Yeh, 2001, "Evolving Traders and the Business School with Genetic Programming: A New Architecture of the Agent-Based Artificial Stock Market," *Journal of Economic Dynamics and Control*, Vol. 25, Issue 3-4, pp. 363-393.

Grossman, S. J. and J. Stiglitz, 1980, "On the Impossibility of Informationally Efficiency Markets," *American Economic Review*, 70, pp. 393-408.

Lucas, R. E., 1986, "Adaptive Behavior and Economic Theory," in Hogarth, R. M. and M. W. Reder (eds.), *Rational Choice: The Contrast between Economics and Psychology*, University of Chicago Press, pp. 217-242.

Vriend, N., 2000, "An Illustration of the Essential Difference between Individual and Social Learning, and Its Consequence for Computational Analysis," *Journal of Economic Dynamics and Control*, Vol. 24, Issue 1, pp. 1-19.

Yeh, C.-H., and S.-H. Chen, 2000, "Toward an Integration of Social Learning and Individual Learning in Agent-Based Computational Stock Markets: The Approach Based on Population Genetic Programming," presented at the Sixth International Conference on Computing in Economics (CEF'2000). Barcelona, Catalonia, Spain. July 6-8, 2000.