# Social and individual learning in *micro economic* framework: choosing an investment

Federico Cecconi * Stefano Zappacosta Davide Marocco
Alberto Acerbi

April 27, 2007

**Abstract**

In the modeling of learning processes a distinction is generally made between individual and social learning. Cognitive science studies both the functioning and the evolution of individual learning. The theory of rational social learning studies how decision makers are influenced by the choices of the others (social learning). We focus on the problems of the interactions between individual and social learning in a *micro economic* framework. In this work agents have to choose two different modalities of investment, with different (and unknow) profitability. We show the effect of different learning procedures during the evolution and at steady state. Besides, we show some correlations between model prevision and herding behavior in finance market.

## 1 The social learning in cognitive economic

There are three main strands of literature that have emerged in the context of learning in economic framework: (i) adaptive procedures based on backward-looking criteria (typically imitation rules); (ii) adaptive procedures based on forward-looking criteria (for example each player keeps track of distribution of own strategies, or the values of own variables, using reinforcement learning). (iii) The third strand is the use of evolutionary procedures. We study the interactions between (i) and (ii) learning model.

In our model $N$ agents may make a choice between three different portfolio (see figure 1):

No investment. We define an agent that makes this choose as ... an agent in $Outer_{Area}$ ...; Investment of type $A$. In this case we said that the agent is in $A_{Area}$; Investment of type $B$ (we said that the agent is in $B_{Area}$). The agents modify own positions (for example from $A_{Area}$ to $Outer_{Area}$) using two different learning procedures:

**(a) individual learning**. If an agent stays in $A_{Area}$ (or in $B_{Area}$) it tends to remain in the same position (if the agent knows $A_{Area}$ tend to remain in $A_{Area}$, vice versa for $B_{Area}$)

**(b) social learning**. The behavior of agents (to stay or to go) is influenced by how many agents stay in the same position at the same time.

The investment of type $B$ is worse than the investment of type $A$. This information is not directly available to agents. We account that the $A$ investment is more profitable than $B$ investment moving ,with $Death_{Rate}$ frequency, agents from $B_{Area}$ to $Outer_{Area}$.

*LARAL, Institute of Cognitive Sciences and Technologies, CNR, Via S. Martino della Battaglia 44, 00185 Roma (RM), ITALY, federico.cecconi@istc.cnr.it

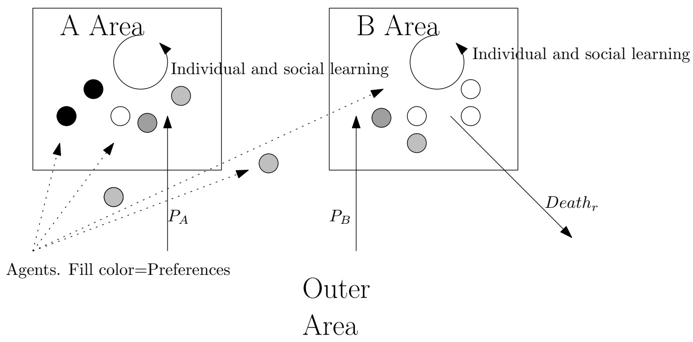


Figure 1: The model. Agents may make a choice between three different portfolio (we said that the agents move in different areas). The color of the agents is the preference (black means $A$ preference).

We describe the dynamics of the system with an $ODE$ system:

$$\begin{cases} \dot{O} = -(P_A + P_B)O + (1 - sigm(\pi_A))A + (1 - sigm(\pi_B))B + Death_{Rate}B \\ \dot{A} = -(1 - sigm(\pi_A))A + P_A\, O \\ \dot{B} = -(1 - sigm(\pi_B))B + P_B\, O - Death_{Rate}B \\ \dot{\pi}_A = \begin{cases} A - B, & Social \\ Lr_A\, sign(A - B), & Individual \end{cases} \\ \dot{\pi}_B = \begin{cases} B - A, & Social \\ Lr_B\, sign(B - A), & Individual \end{cases} \end{cases}$$

$P_A$ and $P_B$ are the probability that an agent moves in $A_{Area}$ (or $B_{Area}$). $\pi_A$ and $\pi_B$ are the average of individual preferences for $A_{Area}$ (or $B_{Area}$). $A$, $B$ and $O$ indicate the density of agents for the respective areas. We use the difference between density ($A - B$ and $B - A$) to adjust the preferences with social learning; we use a fixed rate with individual learning. $logsig$ is the logistic function. We compute dynamics (and steady state) of $ODE$ system with a numerical integration, based on $ODE45$ algorithm in ©$MATLAB$.

## 2 Sketch of results

We obtain interesting results studying the evolution of $A_{Area}$ density with social and individual learning (see for example the figure 2. We find the same regularities modifying parameters and the initial distributions). The social learning is more efficient to find the correct solution (all agents stay into $A_{Area}$). This is an intriguing result, since the presence of agents in $BArea$ is a driving force as far as the agents remain in *wrong* area ....

We study the steady state of the system varying parameters: in figure 3 we show an example of transition point varying $Death_{Rate}$ (see the arrow).

Finally, we confront the numerical simulation results with empirical and *monte carlo* simulation data. In figure 4, we draw the density into the three areas using numerical simulation (solid lane) and *monte carlo* simulation (dotted line).

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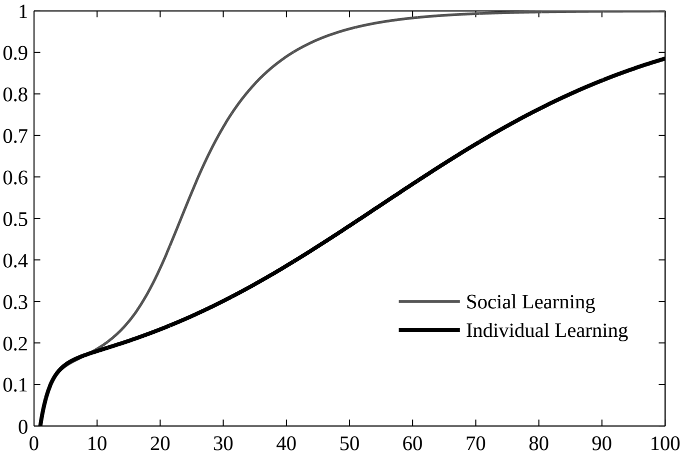


Figure 2: Density in $A_{Area}$.

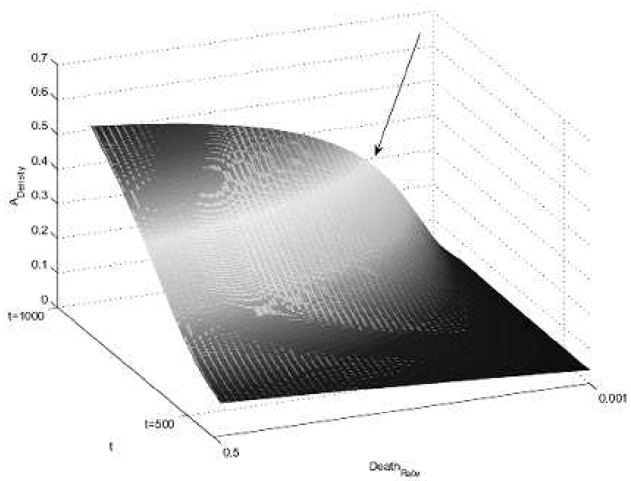


Figure 3: Dynamics of the system varying $Death_{Rate}$.

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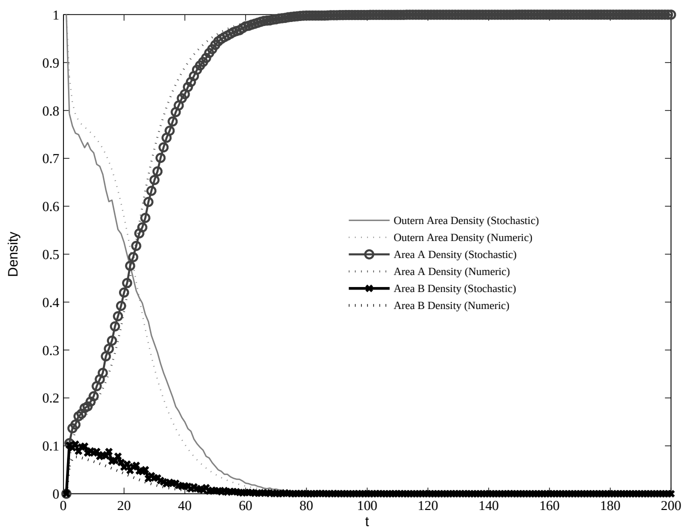


Figure 4: Numerical vs. *monte carlo* simulation