Randomness, Imitation or Reason Explain Agents' Behaviour into an Artificial Stock Market?

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Abstract. This paper shows that the effects of the interaction between simple artificial agents in a well defined economic environments, such as an artificial stock market, are useful to understand microeconomic events. We employ here the connectionist *cross-target* (CT) method [4] to build artificial neural subjects that make (i) guesses about their own actions and (ii) guesses about the effects of those actions. Each subject, learning and acting, develops the coherence between the two types of guesses. Our artificial interacting agents buy and sell shares, following cyclical behaviour (buying when the price rises and selling when the price diminishes) or developing risk aversion or true anti cyclical strategies. The last complex strategy can emerge from imitation between agents and randomness instead of reason.

1 Introduction

We are attempting to explain the behaviour of economic agents by substituting randomness or imitation to rationality. The work is founded on the interaction between simple agents instead of sophisticated representative ones [3]. We will employ the general framework of artificial adaptive agents [1] to make several experiments with two populations of agents. The first population acts with the goal of enrichment; in CT terminology this kind of goal is an external objective, or EO. The second population acts with no goals, but self developing a risk averse attitude on the basis of a simple mechanism generated by the learning; introducing randomness or imitation as suggestions (external proposals or EP) for the actions, unattended rationality emerges. Our agents act and simultaneously learn.

Section 2, after the presentation of the CT technique in a general way, introduces the specification of the equations describing the target for the training in these experiments; Section 3 presents simple results obtained with a stand alone agent, whose action has no counterpart and thus is unlimited; Section 4 is devoted to experiments with two populations of interacting agents, also adopting EP to influence the actions made by the second population. Section 4 also suggests future improvements.

2 The Cross-Target Technique and the Structure of the Model

CT method develops coherence between actions and effects, intended as guesses made by the artificial neural subject. Following also other authors' works [2], the choice of the neural approach is mostly due to the adaptive capabilities of neural functions (here: feed forward multilayer ones). Also genetic algorithms are highly flexible, but mainly if applied to neural network selection. So we here directly apply neural networks to simulate adaptive agents acting and simultaneously learning from their success and errors: the success is identified with the development of the coherence of agents' guesses. Other adaptive function or algorithm could be used, as classifier systems, but with a lack of objectivity in the work: The choice of a specific functional form or structure for classifier systems is less aseptic than neural adaptation. *We stress the fact that we do not have here any a priori economic rule*.

The targets necessary for training the neural network are generated by the artificial agent itself while it learns and acts, going from the actions to effects and from the effects to the actions, in a *crossed* way.

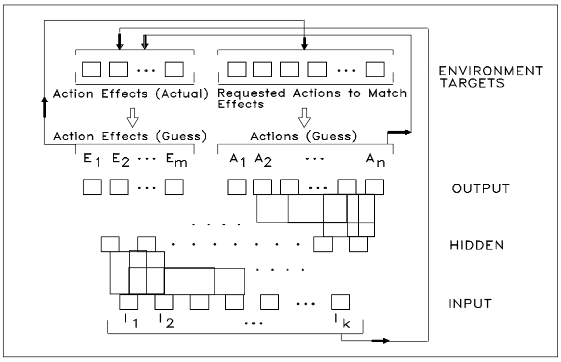

Fig. 1. The connectionistic structure of CT agents

Each neural agent produces (Fig. 1) guesses about both its own *actions* and their *effects*, following an information set (the input elements I_1, ..., I_k). Actual effects are estimated by environment rules on the basis of the guessed actions, taking account also of the consequences of interaction between agents, if any; the results are used to train the mechanism that guesses the effects. The evaluations of the actions necessary to match guessed effects are, on the contrary, employed to train the decision mechanism that guesses actions. In the last case we have to use inverse rules, with problems when the inverse is indeterminate. When the targets for some actions cannot be determinate separately due to the lack of inverse equations, we use a random separation of the inverse correction that is applied to the actions to obtain the desired effects. If one action determines multiple effects, they are included in several environmental accounting definitions; we have therefore more then one possible correction: The one with the largest absolute value is chosen.

EP and EO are external targets: EO substitute the cross one to train the specific output processing element, but the original CT target survives for the crossed training of actions; EP represents one of the multiple targets - from which the highest is chosen - used to train the side of the model that guesses the actions. External proposals suggest actions: in our case one source of suggestion is randomness, which is sufficient in Exp. B to explain in a radical way what apparently could be the effect of the reason. Another kind of EP is imitation, which is a powerful mean to exchange information between agents; imitation, well known by sociologists, but it is almost unknown in economic models, where agents exchange information by prices.

In the models shown here, the inputs of the neural artificial agents are: M_{t-1} , quantity of money at time t - 1; S_{t-1}, quantity of shares at the same time; W_{t-1}, global wealth (money and shares); A_{t-1} , V_{t-1} , A_{t-2}, V_{t-2} quantities of shares bought (A as acquisition) and sold (V as vendor) at the time t - 1 or t - 2; p_{t-3}, p_{t-2} , p_{t-1} prices at the specified time. On the side of the effects (following Fig. 1) the outputs are: Ac_t, Vc_t, guesses about actual contracts of purchase and sale of shares stipulated with another agent (the acts of sale and purchase are kept independent to verify deeply the artificial behaviour of the agents); M_t, S_t, W_t guesses about the effects of the subject's actions at time t. On the side of the actions the outputs are: A_t, V_t, guesses upon quantities of shares that the subject would buy and sell at time t. Globally we have 10 inputs, 13 hidden elements and 7 outputs.

We adopt the following non standard operators:

$H[\ x_1, x_2, \dots x_n\ ] = x_i$, where x_i is the highest x value in module;

C_i, ith random value uniformly distributed in the 0÷1 range; we operate here with twenty subjects; the C operators (as C_{61} in Eqn. 1 or C_{81} in Eqn. 13) are numbered accounting for the presence of the other subjects;

$\{\ i\ n\ s_1\ s_2\ \dots\ s_n\ \}$ list operator number i, that chooses randomly between n subjects, avoiding the choice of the subject itself; the complete list is shown only in the first declaration; in subsequent uses the operator is written in the short form $\{\ i\ \}$; so $V_t\{\ i\ n\ s_1\ s_2\ \dots\ s_n\ \}$, or $V_t\{\ i\ \}$, means the value V_t of one of the n agents, randomly chosen. Several list operators can appear in a model, with different numbers. In each simulation period, or "day", the value of each list operator is kept constant.

The equations describing the targets are noted below; variables preceded by a little star are targets; they are eventually noted on the left with EO or EP. In the following experiments we have twenty agents. The complex notation adopted here is strictly related to the necessity of writing rules for CTs determination.

(1) $^{*}Ac_t = (V_t\ \{\ 1\ 20\ 1\ 2\ 3\ 4\ 5\ 6\ 7\ 8\ 9\ 10\ 11\ 12\ 13\ 14\ 15\ 16\ 17\ 18\ 19\ 20\ \} - A_t)\cdot C_{61} + A_t$

(2) $^{*}Vc_t = (A_t\{\ 1\ \} - V_t)\cdot(1 - C_{61}) + V_t$

(3) $^{*}M_t = {}^{*}M_{t-1} + ({}^{*}Vc_t - {}^{*}Ac_t)\cdot p_{t-1}$

(4) $^{*}S_t = {}^{*}S_{t-1} + {}^{*}Ac_t - {}^{*}Vc_t$

(5) $^{*}W_t = {}^{*}M_t + {}^{*}S_t \cdot p_t$

(6) $^{*}A_t = H\,[(Ac_t - {}^{*}Ac_t), -C_1\cdot(M_t - {}^{*}M_t)/p_{t-1}, C_2\cdot(S_t - {}^{*}S_t), -C_3\cdot(W_t - {}^{*}W_t)/(p_{t-1} - p_t)\,] + A_t$

(7) $^{*}V_t = H\,[(Vc_t - {}^{*}Vc_t), (1 - C_1)\cdot(M_t - {}^{*}M_t)/p_{t-1}, -(1 - C_2)\cdot(S_t - {}^{*}S_t), (1 - C_3)\cdot(W_t - {}^{*}W_t)/(p_{t-1} - p_t)\,] + V_t$

This is the general framework of our agents, with neither EO nor EP. The implicit goal of this cross-target neural model is strictly the development of coherence between the effect side and the action one of the outputs. Everybody acts (buying or selling) at the price p_{t-1}, which is the closing price of the previous day, known by all agents; after the action - at the end of the day - the agents know the ending price of the day (p_t). The meaning of (1) and (2) is that of stating a random matching between the demand and the supply of any couple of exchanging subjects; other solutions (the min value, the arithmetic mean) do not give significant differences.

We can introduce in the model an external objective (EO) like that expressed in (8), with the obvious meaning of improving wealth at a daily fixed rate:

(8) ${}_{EO}^{*}W_t = {}_{EO}^{*}W_{t-1} \cdot 1.0005$

The cross-targets original equation (5) always runs to determine $^{*}W_t$ that is employed in (6) and (7). EO agents adjust the weights with which they guess their actions to improve the capability to make the difference between p_{t-1} and p_t fruitful. Remember that is the last price that is used in the determination of wealth W.

The experiments are conducted on the basis of an exogenous price, generated by a sinusoidal function with min 1.05, amplitude 0.9 and with a random perturbation of ±0.05, giving a complete range 1÷2; the starting price is about 1.5. In the equations (6, 7) the corrections are made upon A_t and V_t values as *proxies* of the correct Ac_t and

-Vc_t values, which are the effects upon which is founded the determination of all the other effects.

3 Independent Agents

The two introductory experiments are based on the independence of the agents. Only the graph of one agent per experiment is shown. All values other than p_t are noted -g*m* where g means guess and *m* is the number identifying the agent. *W-ex-p* (*ex post* value) is obtained, at p_t price, from $^*M_t$ and $^*S_t$. Due to independence of the agents, equations (1) and (2) are substituted by following equations:

(9) $\quad {}^*Ac_t = A_t$

(10) $\quad {}^*Vc_t = V_t$

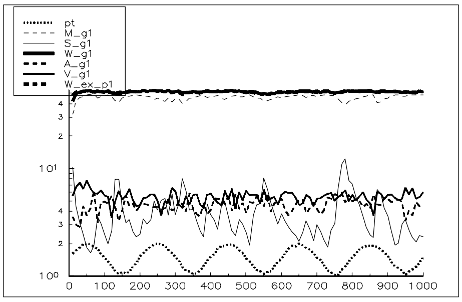

Fig. 2.

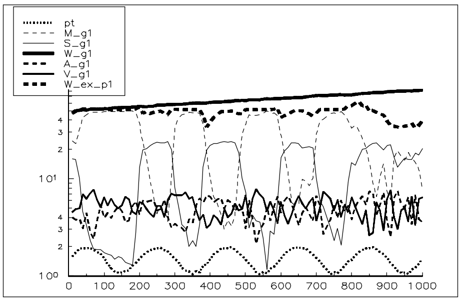

Fig. 3.

To read the Figures 2÷7, we observe mainly the lines *M-g* (guess) and *S-g*, to discover their positive or negative relations with price cycle. Without EO we have (Fig. 2) all the agents acting to avoid risk: They sell all the shares and keep money, so greatly simplifying the task of developing coherence between the guesses of the actions and those of their effects. With EO of Eqn. (8), the agents are compelled to exploit the daily difference between p_{t-1} and p_{t-1} to augment *W* and thus they act in the short term (Fig. 3) selling when the price diminishes and vice versa.

4 Two Populations of Interacting Agents

Introducing the interaction, with twenty agents of two types (one population of ten agents acting with EO and without EP and the other without EO but in four cases with EP) we develop five Experiments (Table 1).

The new equations are the following:

(11) $\quad {}^*A_t = H\,[(Ac_t - {}^*Ac_t), -C_1 \cdot (M_t - {}^*M_t)/p_{t-1}, C_2 \cdot (S_t - {}^*S_t), -C_3 \cdot (W_t - {}^*W_t)/(p_{t-1} - p_t),$
$\quad {}_{EP}z\,] + A_t$

(12) $\quad {}^*V_t = H\,[(Vc_t - {}^*Vc_t), (1 - C_1) \cdot (M_t - {}^*M_t)/p_{t-1}, -(1 - C_2) \cdot (S_t - {}^*S_t),$
$\quad (1 - C_3) \cdot (W_t - {}^*W_t)/(p_{t-1} - p_t), {}_{EP}z\,] + V_t$

(13) $\quad {}_{EP}z = C_{81} \cdot K$; K represents the max. amount of shares that can be daily bought or sold

(14) $\quad {}_{EP}z = A_t$ { 2 20 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 } in (11);
$\quad {}_{EP}z = V_t$ { 2 } in (12)

(15) $\quad {}_{EP}z = A_t$ { 2 10 1 2 3 4 5 6 7 8 9 10 } in (11); ${}_{EP}z = V_t$ { 2 } in (12)

(16) $_{EP}z = H[\ A_t\ \{\ 2\ 10\ 1\ 2\ 3\ 4\ 5\ 6\ 7\ 8\ 9\ 10\ \},\ C_{81} \cdot K]$ in (11);

$_{EP}z = H[\ A_t\ \{\ 2\ \}, C_{81} \cdot K]$ in (12)

In Exp. A the agents of the first population have no counterpart, being the second population risk averse and so are compelled, in the attempt of augmenting W, to keep shares (see Fig. 4).Those of the second population are risk averse, but having no EO are more oscillating in their behaviour, with spurious effect of constant, limited cyclical or limited anti cyclical behaviour (see in Fig. 5 an example of constant behaviour).

Exp.	EP or EO	**Substituting Eqns.** (6) and (7) for the second pop. with ...
A	first population with EO of Eqn. (8) - Second population without EP	no substitution
B	first population with EO of Eqn. (8) - Second population with EP of Eqn. (13), showing the *consequences* of *randomness*	(11) and (12), adopting (13)⌊
C	first population with EO of Eqn. (8) - Second population with EP of Eqn. (14), showing the *consequences* of *generic imitation*	(11) and (12), adopting (14)⌊
D	first population with EO of Eqn. (8) - Second population with EP of Eqn. (15), showing the *consequences* of *specific imitation*	(11) and (12), adopting (15)⌊
E	first population with EO of Eqn. (8) - Second population with EP of Eqn. (16), showing the *consequences* of *generic imitation* plus *randomness*	(11) and (12), adopting (16)⌊

Table 1. The five experiments. ⌊We observe that the value produced by (13) influences (11) and (12) only if it represents the max. value in the H operator.

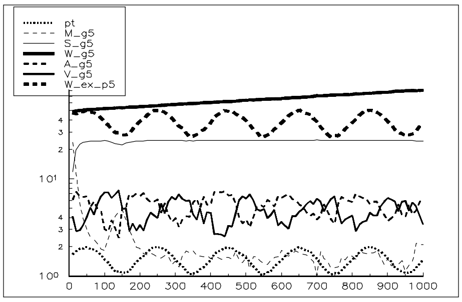

Fig. 4.

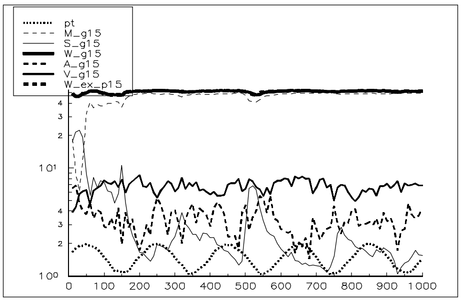

Fig. 5.

Introducing randomness (Exp. B), generic imitation from the second population to all the agents (Exp. C), specific imitation from the second population to the first one (Exp. D) and finally imitation plus randomness, we allow the agents of first population to find a counterpart for their exchanges, showing again the behaviour of Fig. 2; the agents of the second populations imitate or accept random suggestion and buy or sell against their natural risk aversion; then risk aversion newly prevails, determining anti cyclical behaviour (the whole effect is very complex). We show here two representative cases of Exp. E, in Fig. 6 and Fig. 7.

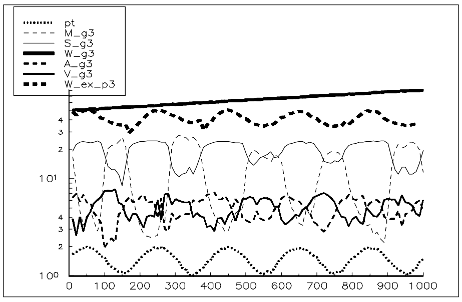

Fig. 6.

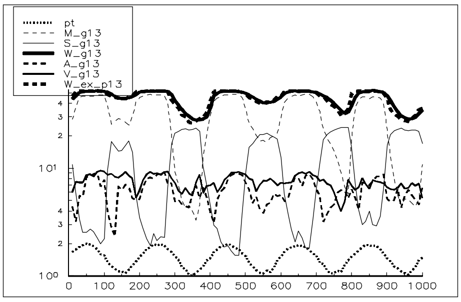

Fig. 7.

Summarising, agents 1÷10 of the first population and agents 11÷20 of the second population show opposite behaviour in almost all the Experiments (Table 2). It is very interesting to consider the importance of both imitation and randomness in the emergence of "rational" behaviour. Notice also that the concurrent effect is almost the sum of the two separated ones; so imitation here is essentially a source of noise as necessary instability of the economic system.

Ag. # .	Exp. A		Exp. B		Exp. C		Exp. D		Exp. E	
	M_g	S_g	M_g	S_g	M_g	S_g	M_g	S_g	M_g	S_g
1÷10	0.102	-0.069	-0.251	0.326	-0.275	0.316	-0.270	0.271	-0.631	0.634
11÷20	0.102	-0.164	0.350	-0.394	0.278	-0.323	0.236	-0.289	0.539	-0.605

Table 2. Mean correlation coefficients between *pt* and *M_g*, *S_g*, first and second population.

We stress the importance of these experiments, explaining what apparently is the consequence of the *reason* as the result of small random shocks and of imitation in a constrained environment. In other terms, *randomness and imitation vs. reason*.

The experiments shown here have been developed on the basis of an original software named CT. The program is under accomplishment and it will allow experiments with an *ex post* learning strategy reflecting the consequences of deep learning upon historical records of the subject's behaviour. Finally, models with endogenous price generation will be also developed.

5 References

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