

Money as a Medium of Exchange in an Economy With Artificial In- telligent Agents

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Introduction

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It turned out to have two consistent equilibria

- Fundamental equilibrium : Good 1 as the medium of Exchange
- Speculative equilibrium : Type 1 also wants good 3

This paper explores the *emergence* of such equilibria with agent-based modeling.

Notations

- $a \in \mathcal{A} = \{1, 2, \dots, A\}$: agent
- At time t , a holds good x_{at}
- Trade with agent $\rho_t(a)$, who holds $x_{\rho_t(a)t}$. $z_{at} \equiv (x_{at}, x_{\rho_t(a)t})$
- a produces $f(a)$
- a receives utility $u_i(i) > 0$ after consumption. (Only consumes its own type)

Decisions: Trade or Not Trade, Consume or Not Consume.

$$\lambda_{at} = \begin{cases} 1 & \text{if } a \text{ wants } x_{at} \text{ for } x_{\rho_t(a)t} \\ 0 & \text{if } a \text{ refuses to trade} \end{cases} \quad (1)$$

$$\gamma_{at} = \begin{cases} 1 & \text{if } a \text{ wants to consume } x_{at}^+ \\ 0 & \text{if } a \text{ not consume} \end{cases} \quad (3)$$

$$x_{a,t+1} = \gamma_{at}f(a) + (1 - \gamma_{at}) \left((1 - \lambda_{at} \cdot \lambda_{\rho_t(a)t})x_{at} + \lambda_{at} \cdot \lambda_{\rho_t(a)t}x_{\rho_t(a)t} \right) \quad (4)$$

Classifier System

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1. Encoding of CS and notations
2. Evolution of strength
3. Genetic algorithm

ENCODINGS FOR A CLASSIFIER SYSTEM I

Code			Meaning
1	0	0	Good 1
0	1	0	Good 2
0	0	1	Good 3
0	#	#	Not good 1
#	0	#	Not good 2
#	#	0	Not good 3

1 : hold

0: not hold

#: either

ENCODINGS FOR A CLASSIFIER SYSTEM II

Define an exchange classifier

Holding of a + Holding of $\rho(a)$ + Trade / Not Trade

total of 3+3+1 codes

$$M_e(z_{at}) = \{e : z_{at} \text{ matches the condition part of classifier } e\} \quad (5)$$

Members of $M_e(z_{at})$ form a collection of potential "bidders". e with the highest strength wins

$$\lambda_{at} = e_t(z_{at}) = \arg \max \{S_e^a(t) : e \in M_e(z_{at})\} \quad (6)$$

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Same for consumption desicion

$$M_c(z_{at}) = \{c : x_{at}^+ \text{ matches the condition part of classifier } c\} \quad (7)$$

$$\gamma_{at} = c_t(z_{at}) = \arg \max \{S_c^a(t) : c \in M_c(z_{at})\} \quad (8)$$

Along with the law of motion in Eq. 4

$$\tau_e^a(t) = 1 + \sum_{s=0}^t I_e^a(s) \quad (9)$$

- $\tau_e^a(t)$: the count of successful trade using the classifier e up to time t .
- $I_e^a(t)$: whether e wins the auction (between classifiers) and helps the agent successfully trade, i.e., $\lambda_{at} \cdot \lambda_{\rho_t(a)t} x_{\rho_t(a)t} = 1$

EVOLUTION OF STRENGTH

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Analogously,

$$\tau_c^a(t) = 1 + \sum_{s=0}^t I_c^a(s) \quad (10)$$

The strength of a classifier is a function of successful wins.

$$S_e^a(t) = S_{e\tau_e^a(t)}^a$$

$$S_c^a(t) = S_{c\tau_c^a(t)}^a$$

Bid-paying Mechanism

Winning classifier e_t^a pays its bids to the winning classifier c_{t-1}^a

Winning classifier c_t^a pays its bids to the winning classifier e_t^a

This mechanism rewards the former classifier that lead to its success, reinforcing the right decision.

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The bid is set as $b_1(e)S_e^a(t)$ for a exchange classifier, and $b_2(c)S_c^a(t)$ for a consumption classifier.

$$b_1(e) = b_{11} + b_{12}\sigma_e \quad (11a)$$

$$b_2(c) = b_{21} + b_{22}\sigma_c \quad (11b)$$

$\sigma. = \frac{1}{1+\text{number of \# 's in the classifier}}$. Higher uncertainty, lower bid.

$$S_{c\tau_c^a(t)}^a = S_{c\tau_c^a(t)-1}^a - \frac{1}{\tau_c^a(t) - 1} \left[(1 + b_2(c)) S_{c\tau_c^a(t)-1}^a - \sum_e I_e^a(t) b_1 S_{e\tau_e^a(t)}^a - U_a(\gamma_{ct}^a) \right] \quad (12)$$

$$S_{e\tau_e^a(t)+1}^a = S_{e\tau_e^a(t)}^a - \frac{1}{\tau_e^a(t)} \left[(1 + b_1(e)) S_{e\tau_e^a(t)}^a - \sum_c I_c^a(t) b_c S_{c\tau_c^a(t)}^a \right] \quad (13)$$

The external payoff after making consumption decision

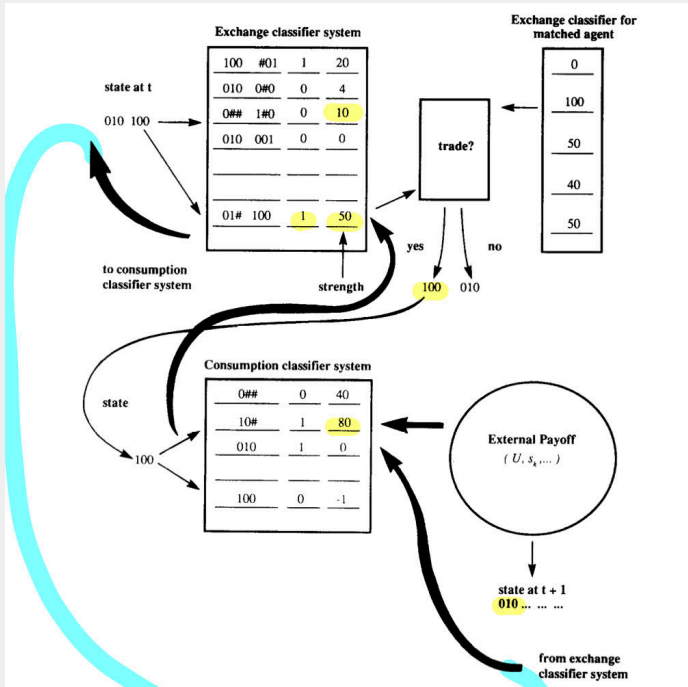
$$U_a(\gamma_{ct}^a) = \gamma_{ct}^a [u_i(x_{at}^+) - s(f(a))] + (1 - \gamma_{ct}^a)s(x_{at}^+) \quad (14)$$

Possible Typo

I think the authors might have a typo here. $(1 - \gamma_{ct}^a)s(x_{at}^+)$ should be a minus since it is the cost of holding.

EVOLUTION OF STRENGTH III

- $S_{e\tau_e^a(t)}^a$ and $S_{c\tau_c^a(t)}^a$ evolves recursively
- Average of past payoff (External reward + bid from other classifier)
- minus payment (bids made to other classifier)
- Only winning classifier pays the bid (the sum term)
- Indexing with counter $\tau_{(\cdot)}^a(t)$: change is made only when successfully winning the auction.



Genetic Algorithm

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- As the variety of goods increase, the state space grows exponentially.
- Impossible to take all enumerations of classifiers into account when initializing.
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Four steps for adding and deleting incumbent classifiers:

1. Creation
2. Diversification
3. Specialization
4. Generalization

Activation

There are no classifier that matches the current state z_{at} , i.e., $|M_e(z_{at})| = 0$.

Action

Assign random action to the current state z_{at} and add it to the collection of classifiers.

DIVERSIFICATION I

Activation

After the matched collection of classifiers $M_e(z_{at})$ are constructed.
If for all $e \in M_e(z_{at})$ have the same action.

Action

Assign opposite action to the current state z_{at} and add it to the collection of classifiers.
Assign the strength of the winning classifier to that of the new one.

There is also a deletion process

Deletion

Remove a "weak" classifier from the set of $M_e(z_{at})$. The weakness is defined jointly with the strength $S_e^a(t)$ and winning counter $\tau_e^a(t)$

Activation

After the winning bit has been determined. Activation probability decreases over time.

The winning classifier has some ambiguous position (#).

Action

Add a new classifier, which changes the #s in the condition part of the current winning classifier with some probability.

If the # is changed, it changes to the correspond value of the state.

Deletion

A weak rule is replaced by the new rule above.

Activation

Called randomly after the above variation steps are conducted.
The activation probability decreases over time.

Initialization

Draw *potential parents* and *potential exterminants*. The probability of drawing depends on some fitness criterion.

GENERALIZARION - MATING

1. Pick two parents to mate
2. Pick two position in the classifier
3. Pick to alter the *inner* or *outer* part of the slicing
4. Inconsistent positions are replaced with ambiguity symbol #

parent 1:	1	0		#	1	0		0	0
parent 2:	0	#		0	1	1		1	1
offspring 1:	1	0		#	1	#		0	0
offspring 2:	0	#		0	1	#		1	1

Fig. 4. The mating process for exchange classifiers who have drawn '3,6' and 'in'.

- 5 Strength is set to be the average of its parents

GENERALIZATION - EXTERMINATING

Remove one of the random selected classifier from the potential exterminants set.

I will report the simulation result next week.

Table 4
Description of the economies.

	Production					Storage cost					Utility u_i^a	Initial CS ^{b,c}	Equil. type ^c
	I	II	III	IV	V	1	2	3	4	5			
A1.1	2	3	1	—	—	0.1	1	20	—	—	100	F	F
A1.2	2	3	1	—	—	0.1	1	20	—	—	100	R	F
A2.1	2	3	1	—	—	0.1	1	20	—	—	500	F	S
A2.2	2	3	1	—	—	0.1	1	20	—	—	500	R	S
B.1	3	1	2	—	—	1	4	9	—	—	100	F	F/S
B.2	3	1	2	—	—	1	4	9	—	—	100	R	F/S
C	2	3	1	—	—	0.1	20	70	0	—	100	R	F
D	3	4	5	1	2	1	4	9	20	30	200	R	—

^aUtility levels u_i are set equal for $i = 1, 2, 3$.

^bCS denotes 'classifier system'.

^c'F' implies fixed enumeration and 'R' implies randomly generated rules.