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Methodological issues for Agent-Based Models in the Social Sciences

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Overview

- Short introduction
- How to conduct Agent-Based Simulations
  - Tools, Identification of striking patterns
- Methods for validating, writing and checking an Agent-Based Model
  - M2M, ODD, Archive - writing and communicating results, informing models in interaction with other methodsc

Short introduction

Why do agent-based models?

- Represent social phenomena using three assumptions:
  - interaction is the basis of social life
  - individuals know very little of their environment
  - social life is dynamic and equilibrium do not exist
- Test assumptions not just through (repeated) observation of reality but thanks to coherent construction (“growing”, “generative”)

Doing models

- Build a model based on assumptions
  - theory, observation, folk knowledge
  - identify relevant actors, level of action, individual learning, influence among agents
- Run the model to understand the influence of parameters
  - measure is central like in any science, and maybe more since there is no "spontaneous observation"
  - what we look for, usually, is the unexpected (otherwise, "why bother simulating?")
- Does the emerging phenomena correspond in any way to the "target system"
  - many possible answers to this question (problem-based)

Agent-based models

- what will differ in ABM is the type of demonstration
- "third way" in between deduction and induction (using both)
- several ways to use it:
  - computer science: use social models to construct more robust models for machine organisation
  - economics: find the algorithm that would represent human rationality
  - geography: explain the apparition of cities with simple hypotheses
  - environment and ecology: companion modelling, applied decision making
  - general social science: theory on epistemology, ontology of humans society, pattern-based approach
  - physics: find all possible situations emerging from certain hypothesis

Types of validation

- show that results correspond quantitatively to recorded data - experiments, surveys
- show that a form, pattern, can be produced systematicaly and understand in which context - qualitative
- find all possible patterns produced from hypotheses (explore parameter space to see all virtual societies)
- show that minimal hypotheses are enough to produce a phenomena - not possible to prove that they are needed with this tool...

How to conduct Agent-Based Simulations

(examples)

Simple tools for learning

- Different platforms exist - RePast, Netlogo, Cormas, Masson
- Using already existing simulations with very good documentation
- Concepts that can be perceived very easily: threshold, feedback, correlation among parameters
- Explaining what happens

Examples

- Rather theoretical results
  - Link to general pattern recognition
  - Link to theory
  - Link to experimental data
- from KISS to KIDS

Dynamic models of segregation (Schelling)

(Journal of Mathematical Sociology, 1971)

Segregation model (Schelling)

- Schelling's great idea: global emergence from local actions and perceptions
- Original paper simulated by hand
- Multiple situations (patterns) separated by a simple threshold
- Example of Segregation: two parameters that interact: density and %-similar-wanted

Segregation model

- several global patterns from very behaviours

  (emergence)

- the choice of one agent can destroy the satisfaction of others

  (feedback)

- influence of %-similar-wanted : increasing, decreasing - identifying patterns (75 - 76%)

  (threshold)

- influence of density of agents: new pattern (1350)

  (correlation among parameters)

Segregation model

- What can be concluded?
  - existence of a system that increases global segregation from a local definition of segregation (emergence)
  - (quantitative) property of the system evolves with the density
  - other parameters could be tested and especially rule of movement - distance (Laurie and Jaggi, 2003) - network shape (Banos, 2010) - anticipation...
- How to use it in real life?

Presentation of the difference between individual and collective learning (Nick Vriend)

(JEDC, 2000)

Central issue

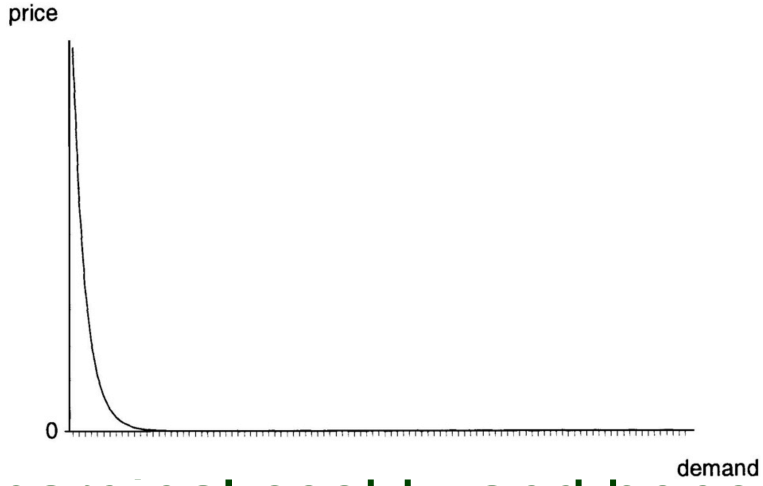
- Shows that the difference in the representation of learning has an impact global result (also see Rouchier, 2001; Galtier, 2002)
- Genetic algorithm to represent learning
- Compares to theoretical results and uses them to explain

Learning

- Two perceptions
    - Individual : own perceptions only
    - Social : collective knowledge
- Relevant data for each individual
    - Individual : own past actions and associated gains (very usual in “individual learning”)
    - Collectives : everyone actions and associated gains

Chosen example

- N firms same good which is sold on one unique market
- Firm i produce qi. Total production is Q.
- Market price depends on Q : P (Q) = a + b.Q^c



- Fix costs K and marginal cost k, and hence total cost: TC (q) = K + k.q
- Firms have to choose how much to produce...

Optimal choices

Profit : $\Pi(q)=[a+bQ^{c}]q-[K+kq]$

- When one firm does not influence the market (large market):

$$d\,\Pi(q)/dq=[a+bQ^{c}]-K=0 \text{ (optimal)}$$

$$Q^{W}=((k-a)/b)^{1/c} \text{ et } q^{W}=Q^{W}/n$$

Walras

- When one firm influences the market

$$d\,\Pi(q)/dq=P+dP/dq-k=[a+bQ^{c}]+d[a+bQ^{c}]/dq-k=0$$

$$Q^{W}=((k-a)/b.((c/n)+1))^{1/c} \text{ et } q^{W}=Q^{W}/n$$

With $a < 0$ $b>0$ $c<0$ and $c-1>-2n$

Cournot-Nash

Implementing in model

- 40 firms learn with GA model
- Rules are not “if... then...” but a bit string that gives production: 11 bits, defining production from 1 to 2048. Initially randomly built and attributed to agents
- For each time-step: choice of production -> gain
- social learning: uses one rule for 100 steps, knows about all other agents associations of the shape [rule > gain]. Revises every 100 steps throuh imitation and recombinaison of best performing rules. Created rules are distributed randomly.
- individuel learning: agent has 40 rules and uses them with a preference for those giving high gain. Revises every 100 time-steps thanks to recombinaison of winning rules.

Pseudo-code

```
start main loop
        for each period do
        begin
                for each firm do Classifier Systems's actions
                begin
                        activerule : "CHOOSE - ACTION;
                output level : "action of active } rule;
                end;
determine market price;
        for each firm do Classifier Systems's outcomes
        begin
                    profit : "(market price) ) (output level)}costs;
                    utility : "monotonic transformation of profit;
                    with active } rule do fitness : "utility;
        end;
if period is multiple of 100 then application Genetic Algorithm
begin
        if individual learning GA then for each firm do
                        GENERATE } NEW } RULES
        else if social learning GA then
        begin
                create set of 40 rules taking the 1 rule from each firm;
                GENERATE } NEW } RULES;
                re-assign 1 rule to each of the 40 firms
        end;
end
```

Pseudo-code

```
INITIALIZATION
for each firm do for each rule do (1 ou 40)
begin
                make random bit string of length 11 with standard binary encoding;
                 fitness : "1.00;
end;
```

```
function CHOOSE - ACTION;
begin
        for each rule do
        begin
                linearly rescale the firm's actual fitnesses to [0,1];
                bid : "rescaled } fitness#e; Mwith e+N(0, 0.075)N
                with probability : "0.025 the bid is ignored;
        end;
determine highest } bid;
end;
choose } action : "highest } bid;
```

Pseudo-code

```
procedure GENERATE } NEW } RULES;
linearly rescale the actual fitnesses to [0,1];
repeat;
        choose two mating parent rules from 30 fittest rules by roulette wheelselection;
        (each rule with probability : "rescaled - fitness/sum (rescaled- fitnesses)
        with probability : "0.95 do
        begin
                place the two binary strings side by side and choose random crossing point;
                swap bits before crossing point;
                choose one of the two offspring at random as new } rule;
         end;
        with new } rule do
        begin
               fitness : "average fitnesses of the two mating parent strings;
                for each bit do with prob. : "0.001 do mutate bit from 1 to 0 or other way round;
        end;
        if new } rule is not duplicate of existing rule
T       hen replace one of weakest 10 existing rule with new } rule else throwaway;
until 10 new rules created;
```

Parameters

Minimum individual output level	1
Maximum individual output level	2048
Encoding of bit string Standard	binary
Length of bit string	11
Number rules individual GA	40
Number rules social GA	40 X 1
GA-rate	100
Number new rules	10
Selection	tournament
Prob. selection	Fitness/Σfitnesses
Crossover	Point
Prob. crossover	0.95
Prob. mutation	0.001

Results

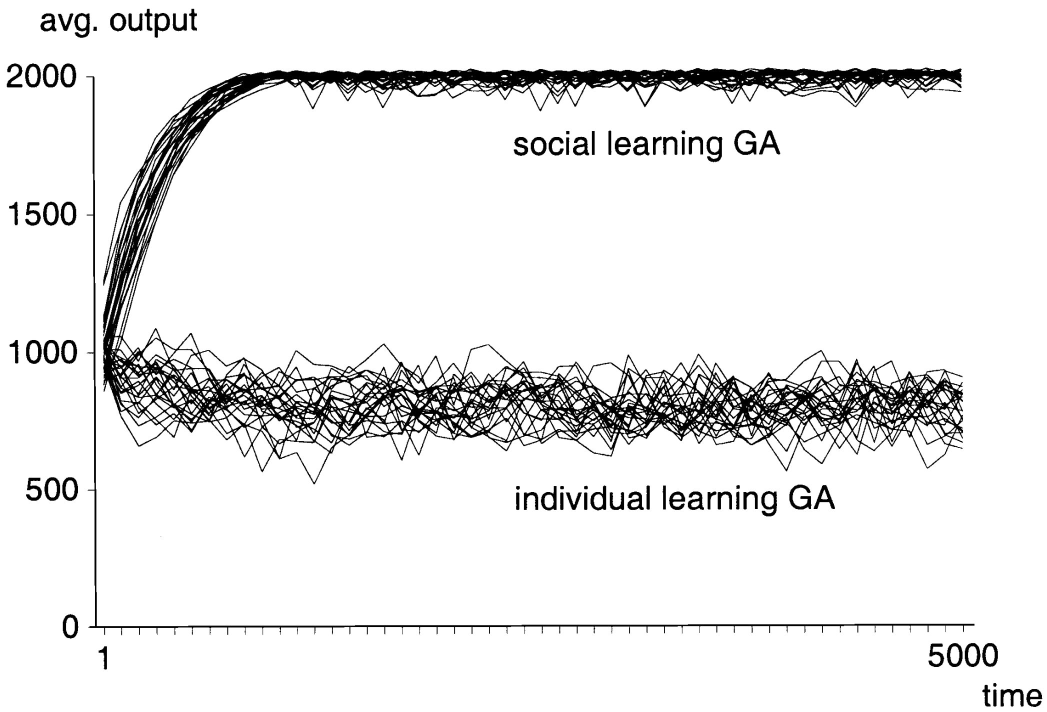


Fig. 5. Average output levels individual learning GA and social learning GA.

Table 1
Output levels individual learning GA and social learning GA, periods 5001–10,000

	Indiv. learning GA	Social learning GA
Average	805.1	1991.3
Standard deviation	80.5	24.7

Analysis

- Link between
  - Individual learning and convergence to Cournot-Nash equil.
  - Social learning and convergence to Walrasian equil.
- Can be explain intuitively by duopoly model (externality or spite effect)

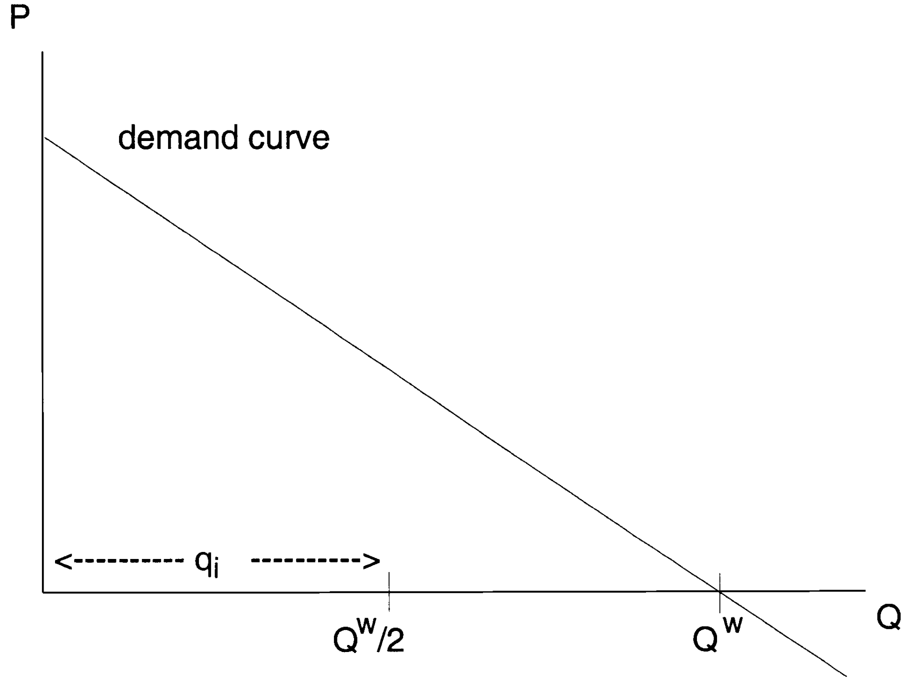
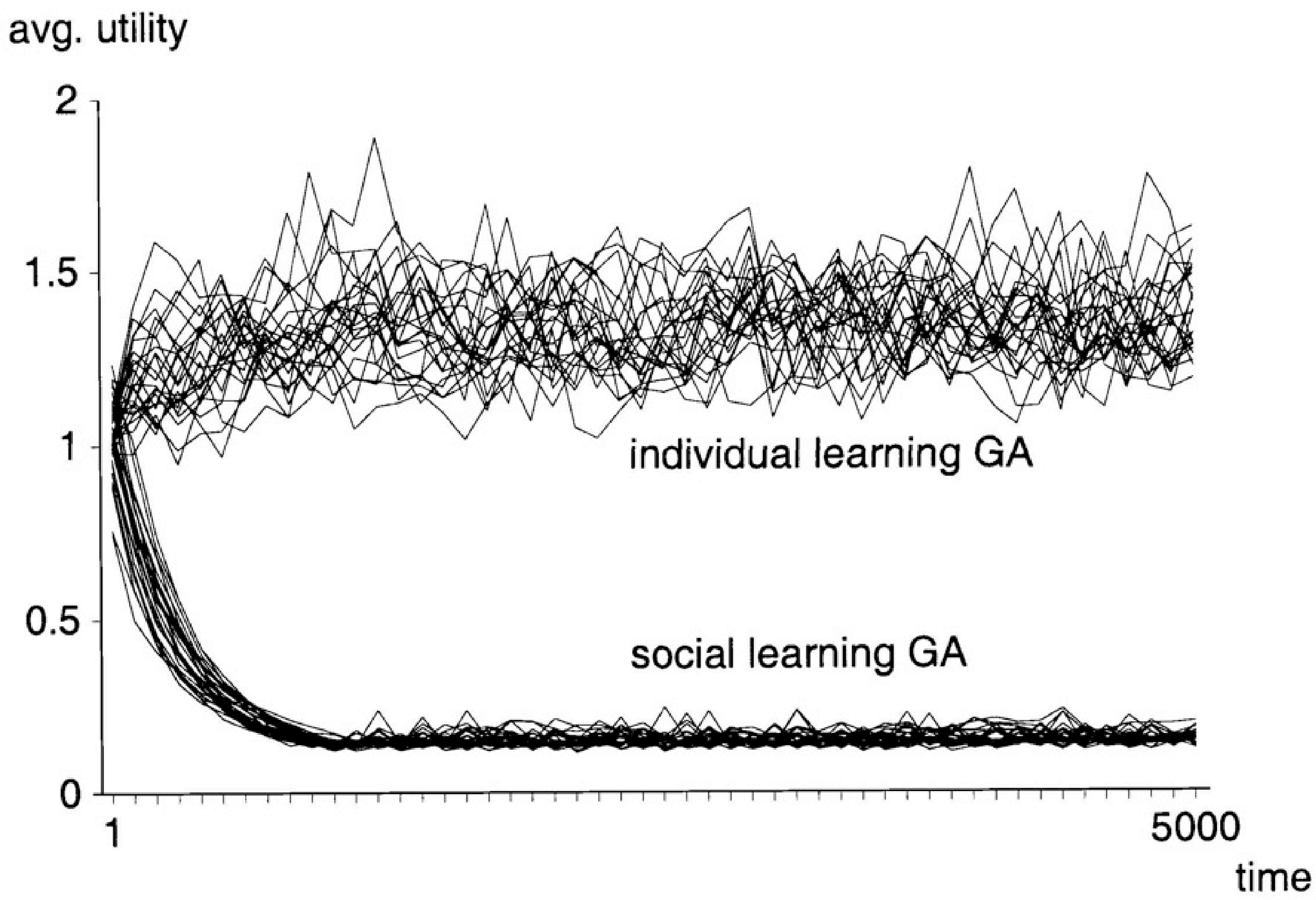


Fig. 6. Example simple Cournot duopoly.


avg. utility
2
1.5
1
0.5
0
1
5000
time
individual learning GA
social learning GA

Analysis

- in terms of utility the individual learning is much better
- it is also more unstable, because of two reasons
  - more permanent adaptation to the behavior of others and larger population of rules in the environment.
  - going from continuous analysis to discrete choices - several equilibrium for one.

Notes

- If n tends to infinity, both equilibrium should match
- one could think about « type learning » - social learning where several agents share the same behavior
- This is not the most usual usage of GA - just a demonstration
- One could hope that another social learning vs individual learning could work - one has to build them as similar as possible - they might not converge to the same values - the explanation might have to be thought again

Conclusion

- Intrisec difference between both learning
- Hence the choice is NEVER neutral
- In economics, the social learning is very often chosen for implementation simplicity - bad idea...
- Theory but no link to emplirical studies

My conclusion

- He shows the feedback of one's choice on the others, through different canals depending on the modelling choices - in economics it is called the externalities - so this is the reconstruction of a social phenomenon which can be observed
- He explains the phenomenon with theoretical analysis, which shows that his result is robust (to do this one has to use probability or combinatorial view)
- Shows that the famous (unsolved) problem of going from continuous to discrete and converse, does have an impact

Learning, signaling and social preferences in a public-good-games (Janssen and Ahn)

Ecology and society, 2006

Finding an algorithm for human rationality

- Why look for the “equation of the world”?
  – identifying relevant information for agents can make policy decisions much more clever (Rouchier, 2001)
  – change the theory - alas succeed in moving a bit the perfect rationality long-living hypothesis
- Most usual method
  – comparing real behavioral data in the most controled context (economic experiments) to simulation results (Duffy, 2001)
  – fitting the parameters defining the algorithm to make it fit the behavioral data

Public good provision game with social dilemna

- N agents participate
- Agents put together part of capital which produces good > equally redistributed whatever contribution
- try to work on learning > repetition
- ω is initial possession at each time-step
- x_i individual contribution
- r is marginal return per agent

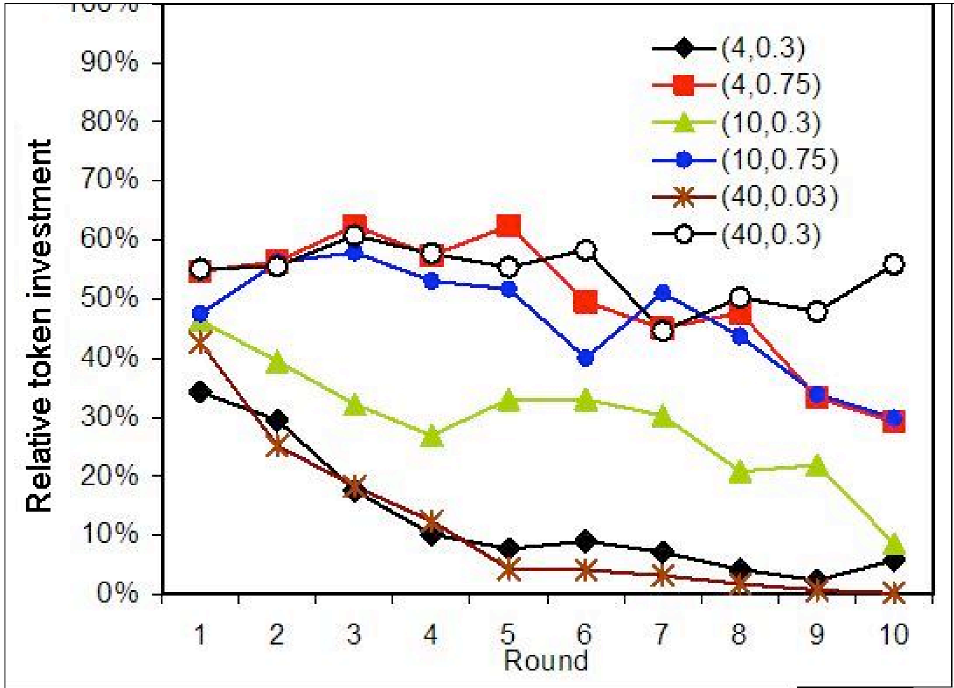
Profit

$$\Pi i = \alpha . (\omega_i - x_i + r . \Sigma x_i)$$

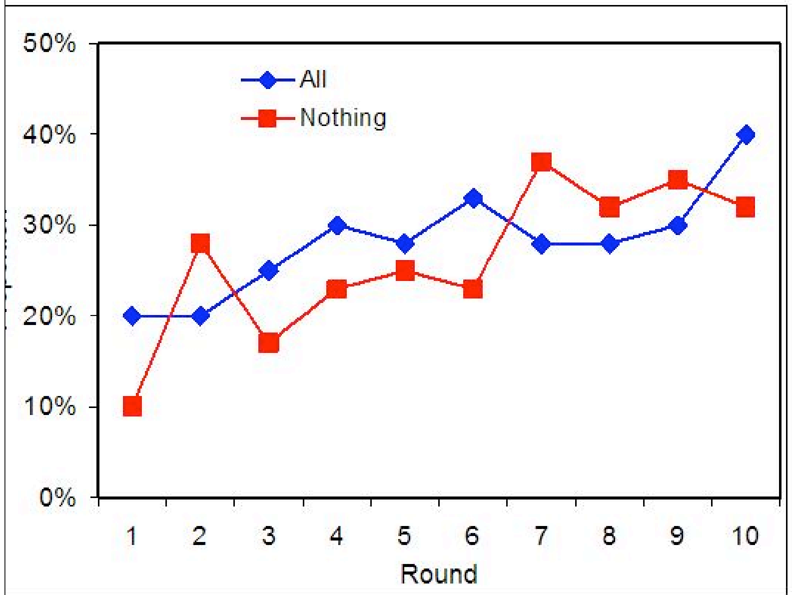
- social dilemna occurs if $r < 1$ and $N.r > 1$
- In all experiments: no one should give anything
- In all experiments: most people do participate

Stylized facts based on experimental results

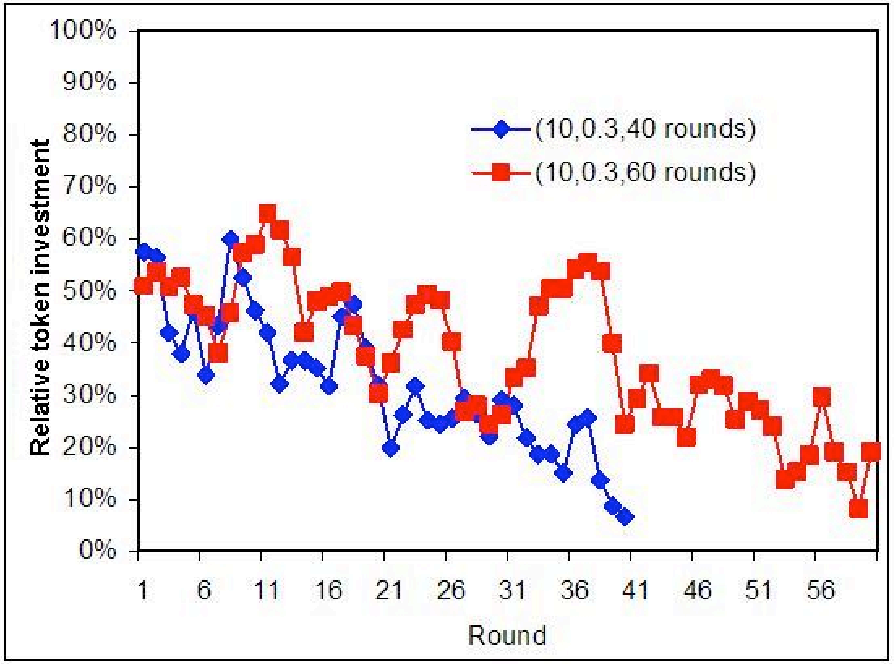
- average contribution depends on size of the group, MPCR (r) and length of the experiment
- for a given average contribution, the variation of individual contribution is huge: 70% give all or 0
- agents change contribution almost at each step - variation and its direction varies - depends on the number of agents and number of steps left



(4,0.3)
(4,0.75)
(10,0.3)
(10,0.75)
(40,0.03)
(40,0.3)
Relative token investment
Round



All
Nothing
Round



(10,0.3,40 rounds)
(10,0.3,60 rounds)
Relative token investment
Round

Learning model

- very usual to represent individual learning in economics (with variations) (Roth-Erev, EWA)
- list of possible actions and choice among those
- model in two parts:
  - probabilistic choice for chosing an option
  - evaluation of each option depending of past individual results “learning”

Probabilistic choice

- $P_{ix} = \exp(\varphi_i . A_{ix}) / \Sigma_\omega \exp(\varphi_i . A_{ix})$

- A is attraction associated to each x (action)
  - if it increases the tendency to choose this specific action increases
- φ sensitivity or discrimination parameter
  - if it increases, two actions with different attractions will have more different probability to be chosen

Basic EWA learning

- learning is the evolution of A_{ix}
- H is the influence of the past
- $H(t) = H(t-1).\lambda_i.(1-\kappa_i) +1$
- λ_i is forgetting, κ_i is the increase rate of A (influence of experience)

  $A_{ix}(t) = (\lambda_i.H(t-1).\ A_{ix}(t-1)+ [(\delta_i+(1- \delta_i).I(x_i,x_i(t))].u_i(x_i,x_{-i}(t))/H(t)$

Social preference

- comparison of my own preference compared to others'
- $U_i = \rho.moy(\pi_{-i}) + (1-\rho).\ \pi_i$ si $\pi_i >= moy(\pi_{-i})$
- $U_i = \chi.moy(\pi_{-i}) + (1-\chi).\ \pi_i$ si $\pi_i < moy(\pi_{-i})$
- $\chi < \rho < 0$ - don't like others to have higher gains
- $\chi < 0 < \rho < 1$ don't like inequality
- $0 < \chi < \rho < 1$ social welfare : want others to be as well
- $0 = \chi = \rho$ no interest about others

Signalling

- Signal = $x_i .r.\theta_i.(T-t/T)\eta_i$
- depends on remaining time and θ_i is the hope one has one its own influence

Rationalité et paramètres

$$A_i^x(t) = \frac{\lambda_i H(t-1) A_i^x(t-1) + [\delta_i + (1-\delta_i) I(x_i, x_i(t))](u_i(x_i, x_{-i}(t)) + x_i \cdot r \cdot \theta \cdot \left(\frac{T-t}{T}\right)^{\eta})}{H(t)}$$

$$P_i^x = \frac{e^{\varphi_i \cdot A_i^x}}{\sum_{j=0}^{\omega} e^{\varphi_i \cdot A_i^x}}$$

$U_i = \rho \cdot \bar{\pi}_{-i} + (1-\rho) \cdot \pi_i$, if $\pi_i \geq \bar{\pi}_{-i}$ and

$U_i = \chi \cdot \bar{\pi}_{-i} + (1-\chi) \cdot \pi_i$, if $\pi_i < \bar{\pi}_{-i}$ and

$$H(t) = H(t-1)\lambda_i(1-\kappa_i) + 1$$

Parameter	Interpretation
ρ	Weight to others' payoff when $\pi_i > \bar{\pi}_{-i}$
χ	Weight to others' payoff when $\pi_i < \bar{\pi}_{-i}$
φ	Response sensitivity
λ	Forgetting rate
δ	Weight to forgone payoffs
κ	Rate of attraction growth
θ	Signal weight
η	Weight of future rounds in signaling

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Testing the model

The aim is (remember): to establish the equation that represents individual rationality

- Three tests
  - “representative agent”
  - individual
  - categories
- statistics: fit is L and k = 8 parameters

  -- AIC = -ln L +2k

  – BIC = -lnL +k lnN

Representative agent

- Several models are tested
  - only EWA
  - SP + EWA
  - SP + EWA + Signalling
- Results
  - SP + EWA + Signalling is best
  - λ= 0.85 et δ=0.55 à 0.72 not optimisers
  - in experiments with 10 steps - signalling is important at start but fades away
  - Longer effect in 40 and 60 simulations

Categories

- EWA + SP + Signalling
- increase the number of categories until it fails
    - 8 categories for 10 steps
    - 2 categories for 40-60 steps

Individuals

- Uniform distribution of each value for parameters
- for each learning find SP and type of learning
- Most of them are belief learner (interested in “what if”)
- Most of them don’t like inequality
- 10% are simple optimizers

My conclusion

- Interesting negative results - optimizing learning agents are minority
- Correlation: no way to find THE algorithm for representing rationality - categories (even facing extremely simple problem)
- One of the ways to link “real world” to simulation results
    - well controlled behaviours (information circulation)
    - simple setting
    - easy to observe and create indicators

Methods for writing, checking, validating an Agent-Based Model

Several dimensions to take into account

- Finding the added value of the work - why bother simulating?
- Running the model and understanding it
- Validating
    - what is inside the model (informing)
    - M2M approach for verification
- Presenting results (ex : ODD)

Reasons to build model (KISS or KIDS)

- Show influence of individual rationality on a global phenomena, when institution is stable
- Influence of institution, rationality being stable
- Look for representations of human behaviors
- Show that simple hypothesis can be enough to explain a phenomena (to get rid off usual badly justified explanation)
- Show that a strategy is “better” than an other
- See the influence of communication mode, networks
- Use model in a participatory process / legitimation

Informing model

- Behavioral model and institution
  - set of possible actions - mandatory or chosen
  - set of possible interactions
  - way(s) to choose among alternative
  - fixed set of choice or learning, imitation,...
- Type of emerging data which is expected - to compare to (depends)
  - small range - abstract models or general ideas (KISS)
  - middle range - stylized facts, regularities in specific setting
  - explicit - complex observed data (KIDS)

Behavioral data

- Literature (can be recommended at start)
- Experiments
- Interviews

- The main problem is formulation: very few sciences produce data of the type “if ... then...”.
  - Adapt statistical data
  - Include specific questions when access to survey

Observation: one simulation

- The most basic data about the central question - MEASURE (prices, quantities, number of links, opinion, segregation, inequalities, production, satisfaction...)
- Usually one needs intermediate indicators and need to be very creative - frequency, agregate or disagregate

  >> Identify patterns in final data and in dynamics

  >> Relevant patterns for outside world (qualitative or quantitative)

Sensitivity analysis / stability of results

- Simulation results are usually sensitive to **parameter settings** of the corresponding model and especially to the **algorithm used to model the agents' behaviour**.

This is part of the internal process for knowing the model. It is a necessary step, considering the number of parameters usually at stake.

Note: reading papers for conferences, one can note that this is not always achieved.

- Helps understand the reasons why things take place - "externality" - whatever shape it takes - is a very usual answer to the question "**why**"

Important step: to go from description to understanding / from correlation to process

Note : it usually helps connecting to "target"

Usually forces to be creative to build new indicators > feed back can be challenging for the field study

Sensitivity analysis

Izquierdo et. al. 2007: mathematical analysis to study sensitivity in their social dilemma model. Replication of Flache model. Different learning rates (fast > reach asymptotic results) and the introduction of stochasticity (destroys predictible equilibria)

Takadama et al. 2007: study the rationality of agents: internal logic + global behaviour. Comparison with human subject experiments.

Kluver and Stoica, 2003: Cellular Automata, Neural Networks and Genetic Algorithm implemented in the same framework (following tradition, they are used in different . Here they succed in converging to the same global model.

Janssen and Ahn, 2003, 2006: Analysis of the influence of the learning algorithm / attempt to fit to data from experimental economics, so that to “evaluate the validity” of different algorithms. WA, fictitious play, learning direction. Results not so positive.

Validation

- One of the most tricky issue
  - discipline-related
  - question-related
  - your answer might not please anyone
  - for example: fitting “real statistical data” can please many people but will rarely please me

Accuracy to represent « outside world » (fitting to data)

Or

Help to understand general dynamics (build models of possible micro-macro links)

Validation

- Theoretical explanation / logical
- “In line” with other types of data
- Useful model - in particular participatory approach: “disposable model” which should not be use outside of its context (usually KIDS)

Accumulation

- Not just in relation with external data and disciplines
- Also discussions among models within the ABM community
- How things can be anticipated because they are structural results (ie. certain ways of coding will give certain types of results (reputation))
- Still open questions -(ie. Role of scale - increase - reduce size)

Aims of M2M workshop

- The first model-to model workshop's aim was to increase the transfert of knowledge (model and results) in agent research -
- Following model-to-model workshops were set up with a view to gathering work on comparative analysis of social simulations.
- 3 workshops where participants provided methods and examples to stop "working on your own model"
- http://jasss.soc.surrey.ac.uk/6/4/11.html

Cross-paradigm comparison

- MABS can be used to better understand **existing models** by implementing agents following such models but relaxing previous constraints (ie homogeneity) [Vila, 2007 – in Bertrand competition reproduces analytical results]
- Social simulation models are **compared** with models developed in alternate paradigms, e.g. equilibrium models, or social theoretical models. (economics and game theory)
- **<u>KISS vs KIDS: </u>choice** between building a very simple agent model that can be compared to a formal analysis but contributes little understanding to empirically observed social phenomena, and a more applicable agent-based model that includes a lot of heterogeneity and learning but is far from tractable analytically.

Cross-paradigm comparison

- For example [Edwards et al. 2003] align top-down with bottom-up models: : develop innovation diffusion (Young 1999). The equation-based model provides an explanation (local maxima and hence attractor basins of the agent model. if more than one attractor, the equation-based model (being deterministic) gets trapped in the minority basin, whilst the individual-based model would eventually escape from this to the principal attractor due to is stochastic nature
- Vriend, 2000 (out of M2M): “local learning vs global learning” - Cournot -Nash equilibrium vs Walras. (global = social comparison learning)

Replication / aligning

- Replication: Rewriting models that others have described in papers so as to understand them more deeply and reproduce the stated results (Axelrod 1997). check if the same theoretical model gives the same results
- « aligning »: check if models that are supposed to give same results do so (Axtell et al. 1996)
- accept the fact that we are closer to experimental science than formal one

- Edmonds and Hales 2003: "tags" model (Riolo et al. 2002) re-implemented on different platforms and aligned (or docked) their models before comparing their results with the previously published results. "double" implementation >> single re-implementation. However, the process of duel implementation helped to uncover inaccuracies in the original interpretation placed on the model by Riolo et al. Indeed they claim to have invalidated the central claim the model was published to support.

Replication

Rouchier 2003: re-implementation of Duffy's paper (2001) which is an agent-based version of a model proposed by Kiyotaki and Wright (1989). Suggestions concerning reporting simulation work, including:

- Algorithm: when the main hypothesis is about learning, it would be useful to have adequate data about the knowledge of the agents and its evolution in time, so as to be able to judge the degree of misrepresentation and its importance;
- Results: it would be useful to give more detailed lists of individual behaviours (not just averaged data) so as to be able to compare processes;
- Results: it is essential to give a genuine description of the dynamics of the model, with different indicators (and not just the one that is most central to the issue) so as to help the aligning of future models and aid the comprehension of the logical processes in the system.

Problem of

- understanding
- trust

Multi-scale analysis, abstraction, models of models

Quality of results? what is the result? added value? generality?

- Models are compared at various spatial, organisational or temporal scales, sometimes using a simple model as an abstraction of a more complex one.
- **Abstraction** is important to the social sciences, particularly where different case studies can be abstracted to grow models and meta models that can be exploited to develop more general theories (Przeworksi and Teune 1970; Cioffi-Revilla 2002).
- General issue in MAS (Gilbert): several models can give same “results” (depending on indicators, of course) > how do you differentiate among them?

Taxonomy and classification

Taxonomy and classification are often known as "systematics" in other fields, such as biology. Here models are grouped into common classes. This is a potentially fruitful line of enquiry, as yet little explored in social simulation, particularly if certain classes of models can be shown to have specific expected results.

However, the systematics of complex models such as most social simulations (which are dynamic, depend on initial conditions, and usually have a large number of parameters) is difficult to achieve through intuitive reasoning alone

Taxonomy and classification

Cioffi-Revilla and Gotts (2003): TRAP² class to analyse two models: GeoSim, a model of military conflict and FEARLUS, a model of land use and ownership change.

Grimm 2006: ODD http://www.ufz.de/oesatools/odd/

ECOLOGICAL MODELLING 1

Overview	Purpose
	State variables and scales
	Process overview and scheduling
Design concepts	Design concepts
Details	Initialization
	Input
	Submodels

ODD - overview

- **Purpose** (introduction - as clear as possible) > helps understading
  - which parts are included or ignored
  - what to expect
  - why you need a complex model
  - what you will do with it

- **State variables and scales**
  - structure of the model system (low-level entities, hierarchical levels, temporal and spatial resolution)
    - Agents
    - spatial units (grid cells)
    - environment (température, price, régulation)
    - collectives (groupes, networks) if they have independent life
  - state variables (or "attributes") - which units - what is calculated from state variables -
  - possible values - usually presented in a table

- **Process overview and scheduling** (verbal, conceptual description of each process + equations + possibly list)
  - processes built into the model; examples are production, feeding, growth, movement, mortality, reproduction, disturbance events, management.
  - scheduling of the model processes (present a flow chart or pseudo-code and justify) : upadte of variable, interactions + discrete or continueous + synchronous or asynchronous processes + random order

ODD - design concepts

- **Emergence**. What is due to emergence and which is directly due to specifications? Which hypothesis has a huge impact?
- **Adaptation**. Do agents have adaptive traits = decision rules and changes of behaviour that change with external or internal state? is it linked to an internal state or is it correlated (observed) to this state?
- **Objectives**. What is success (if there is: “fitness”, “utility”, “success”) / individual or collective - useful information for agents - alternative, criteria
- **Learning**. Does agent learn to adapt? How?
- **Prediction**. Do they anticipate implicitly or explicitly, what, based on personnal or global information?
- **Perception**. What do agents need to reason - internal/external states, agregate, signals from others? Are network of perception emerging or pre-built? Active search or implicite knowledge?
- **Interaction**. Directe or indirecte (message vs competition). Shape (language)
- **Stochasticity**. How much? Results are stable although there is randomization. Why choose random - variability and known frequency? unknown data?
- **Collectifs**. Do agents belong to group that impact on them? Are their organization levels? Entities?
- **Observation**. What is kept? Global, individual, a few data or all?

- NOTES: Not all is necessary, but asks most of the questions that can be answered - most of them being typically agent-based - can be redundant with the overview.

ODD - details

- Initialisation - all initial values - always the same or varies? arbitrary choice or based on data? (REF) - important for re-implementation

- Inputs (where do they come from)
  - in time - precipitations, prices, any entry data that can be observed in time-series and which are inputs
  - in space - spatial patterns of culture, management regimes - use of GIS can be needed when the imposed data are too complex

- Sub-models
  - mathematical skeleton - equations that define change of state variables or rules - parameters should be explained, but no need for verbal explanations
  - If there is room, same model, but with explanations and justification for each mechanisms.

Reuse – Standards ?

Composing models where different scales // different approaches are inter-related in a larger model - the results of one model being used in the other

Outside standard simulation libraries, such as Swarm, RePast or MASON, very little of this is done.

Kahn 2007: Uses libraries of ‘micro-behaviours’ in NetLogo and shows how a simulation can be built up, and different micro-behaviours compared for their effect on the dynamics of the model.

Rouchier and Tubaro, 2010: one (more) study of the Deffuant model

Problem of the reusability // supposed to be easy with object-oriented programming but lack of documentation. >> Marco Janssen et al. 2007 Open Agent Modelling Consortium. http://www.openabm.org/site/

Where is M2M going?

~~"Good modelling practices"~~

~~"Good social science"~~

Accumulation of knowledge

Proper description of models

Replicated results for robustness

....

Validation? (help to understand abstract dynamics)

http://m2m2007.macaulay.ac.uk/m2m_programme.html

http://jasss.soc.surrey.ac.uk/6/4/11.html

Remaining problems

- Main critics
  - impossible to show unicity of the way to get to a result
  - Still hard diffusion of information through papers - ambiguity - no unicity or implementation
  - “ad hoc” model - how to accumulate?
  - sometimes depends on the pseudo-random generation
  - fit to data is still an unsolved issue
- Solve the problems in a collective way
  - open archive (open abm) - replication - cross validation
  - ODD, use of popular plateform