AGENT-BASED MODELS

AB Models are used where the interactions are decentralised, and the autonomous agents make their own decisions (perhaps constrained).

∴ AB models are suitable for interactions which are *bottom-up*, not *top-down.*

∴ social and market interactions, rather than engineering or internal organisational interactions.

>

Using AB models

In ABM/ACE models, a population of software objects is:

- **— instantiated, and each agent is given**
- **— certain internal states (e.g., preferences, endowments) and**
- **— rules of behaviour (e.g., seek utility improvements).**

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— rules of behaviour (e.g., seek utility improvements).

The agents are then permitted to interact directly with one another and a macrostructure emerges from these interactions.

Patterns Emerge

Patterns in this macrostructure may then be (Axtell, 2005):

- **compared with empirical data,**
- **to revise agent internal states and rules, and**
- **the process repeated until an empirically plausible model obtains.**

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e.g. ACE stock markets have been used to model heterogeneous agents: will the stylised features of such markets emerge? Yes.

What is an Agent?

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Another example of an agent that won $2,000,000 in a challenge by the U.S. Department of Defense in October 2005 ...


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Agents and agency

Wooldridge & Jennings (1995) would give computer agents these properties:

- **autonomy: no others control their actions and internal state,**
- **social ability: can interact and communicate with other agents**
- **reactive: they perceive their environment and respond**
- **pro-active: they initiate goal-directed actions**
- **(intentionality: metaphors of beliefs, decisions, motives, and even emotions)**

Eight Desired Attributes of Modelled Agents (G&T)

1. **Knowledge & beliefs.**
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3. **Social models.**
   Agents, knowing about interrelationships between other agents, can develop a "social model", or a topology of their environment: who's who. etc.

Eight Desired Attributes ...

4.

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4. **Knowledge representation.**
   Agents need a representation of beliefs: e.g. predicate logic, semantic (hierarchical) networks, Bayesian (probabilistic) networks.

   > **[Sebastian] Thrun [leader of the winning team in the 2005 DARPA Grand Challenge] had a Zen-like revelation: "A key prerequisite of true intelligence is knowledge of one's own ignorance," he thought. Given the inherent unpredictability of the world, robots, like humans, will always make mistakes. So Thrun pioneered what's known as probabilistic robotics. He programs his machines to adjust their responses to incoming data based on the probability that the data are correct. — Pacella (2005).**

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8. **Emotions.**
   Emergent features? Significant in modelling agents? Or epiphenomenal?

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Since then, five approaches:

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2. **Object Orientation**
3. **Language Parsing & Generation**
4. **Machine-Learning Techniques, and (most recently)**
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Ignore 3., 4. last lecture, 5. too new.

Production Systems

Contain:

1. **a set of rules (a condition + an action),**
2. **a working memory, and**
3. **a rule interpreter (is the condition satisfied? if so, act)**

No prespecified order of rules: contingent.

The agent's designer specifies how to break ties among rules.

Object Orientation

In "object-oriented" programming languages:

- **"objects" are program structures containing data + procedures for operating on those data;**
- **the data are stored in "slots" inside the object;**
- **the procedures are called "methods";**
- **objects created from templates called "classes";**
- **classes are ranked in a hierarchy, with subordinate classes more specialised.**

Modelling pedestrian flow.

e.g. Pedestrian flow in a shopping mall —

- **Class: pedestrian;**
- **Slots: location, direction, gait;**
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OO computer languages: C++, Lisp, Java. etc.

Probabilistic Robotics

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Results: “Stanley,” Stanford’s robotic Volkswagen Touareg beat the field, completing the 132-mile race with a winning time of 6 hours 53 minutes and 58 seconds (an average speed of 19.1 mph). Four other vehicles successfully completed the race. All but one of the 23 finalists in the 2005 race surpassed the 7.36 mile distance completed by the best vehicle in the 2004 race.

Grand Challenge Rules

- The vehicle must travel autonomously on the ground in under ten hours.
- The vehicle must stay within the course boundaries as defined by a data file provided by DARPA.
- The vehicle may use GPS and other public signals.
- No control commands may be sent to the vehicle while en route.
- The vehicle must not intentionally touch any other competing vehicle.
- An autonomous service station is permitted at a checkpoint area approximately halfway between start and finish.

The Stanford team won the first prize of US $2,000,000 in 2005.

Modelling the Environment

Definition of the environment depends on what is being modelled.

For individuals:

- **move in a space, or on a network;**
- **use sensors to perceive the environment, including other agents;**
- **perhaps be able to affect the environment directly;**
- **perhaps receive and send signals in the environment.**

For computer agents, the order of agents running can be crucial (“concurrency”). Sometimes, buffering their signals is sufficient.

G & T Use NetLogo to build a multi-agent simulation.

Economic Journal June 2005 Feature —

- focussed on Complex Adaptive Systems CAS in economics
- appeared just after Leombruni & Richiardi asked, "Why are economists sceptical about agent-based simulations?" (*Physica A* 355: 103–109, 2005.)
- included 4 papers: introduced by Markose, with papers by Axtell, Robson, and Durlauf
- addressing, respectively,
  - — markets as complex adaptive systems,
  - — formal complexity issues,
  - — the co-evolutionary Red Queen effect and novelty, and
  - — the empirical and testable manifestations of CAS in economic phenomena.

Leombruni & Richiardi's answer:

(From 1970, only 8 ACE articles of 26,698 in top 20 economics journals.)

Possible reasons:

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Possible reasons:

- i. **interpretation of the simulation dynamics and generalization of the results,**
- ii. **estimation of the simulation model**
- iii. **I would add: in general, *no necessary conditions* from simulation, just sufficient conditions**
- iv. **and validation of the model.**
  (but also applies to closed-form models)

Markose and the *EJ* Feature on CAS:

- many “anomalies” not understood or modelled using conventional optimisation economics:
  - — innovation,
  - — competitive co-evolution,
  - — persistent heterogeneity,
  - — increasing returns,
  - — “the error-driven processes behind market equilibrium,”
  - — herding,
  - — crashes and extreme events such as October 1987.
- need the “adaptive or emergent methods” of ACE simulation

Moreover ...

Axtell (2005) argues that:

- **the decentralised market as a whole can be seen as a collective computing device**
- **the parallel distributed agent-based models of *k*-lateral exchange → the specific level of complexity (polynomial) in calculations of equilibrium prices and allocations.**

Simon’s Bounded Rationality

Agent-based models, following Simon (1982), also assume Bounded Rationality. Indeed, in the absence of Turing machine (universal calculator), it is difficult not to.

But Epstein (2006) reflects:
“One wonders how the core concerns and history of economics would have developed if, instead of being inspired by continuum physics ... blissfully unconcerned as it is with effective computability — it had been founded on Turing. Finitistic issues of computability, learnability, attainment of equilibrium (rather than mere existence), problem complexity, and undecidability, would then have been central from the start. Their foundational importance is only now being recognized.

Epstein on the virtues of boundedly rational agents ...

“As Duncan Foley summarizes:

> **`The theory of computability and computational complexity suggest that there are two inherent limitations to the rational choice paradigm.**
>
> **One limitation stems from the possibility that the agent’s problem is in fact undecidable, so that no computational procedure exists which for all inputs will give her the needed answer in finite time.**
>
> **A second limitation is posed by computational complexity in that even if her problem is decidable, the computational cost of solving it may in many situations be so large as to overwhelm any possible gains from the optimal choice of action.’ (See Albin 1998, 46).”**

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