

Agent-Based Modeling



A Third Way of Doing Science

Two traditional ways of doing science

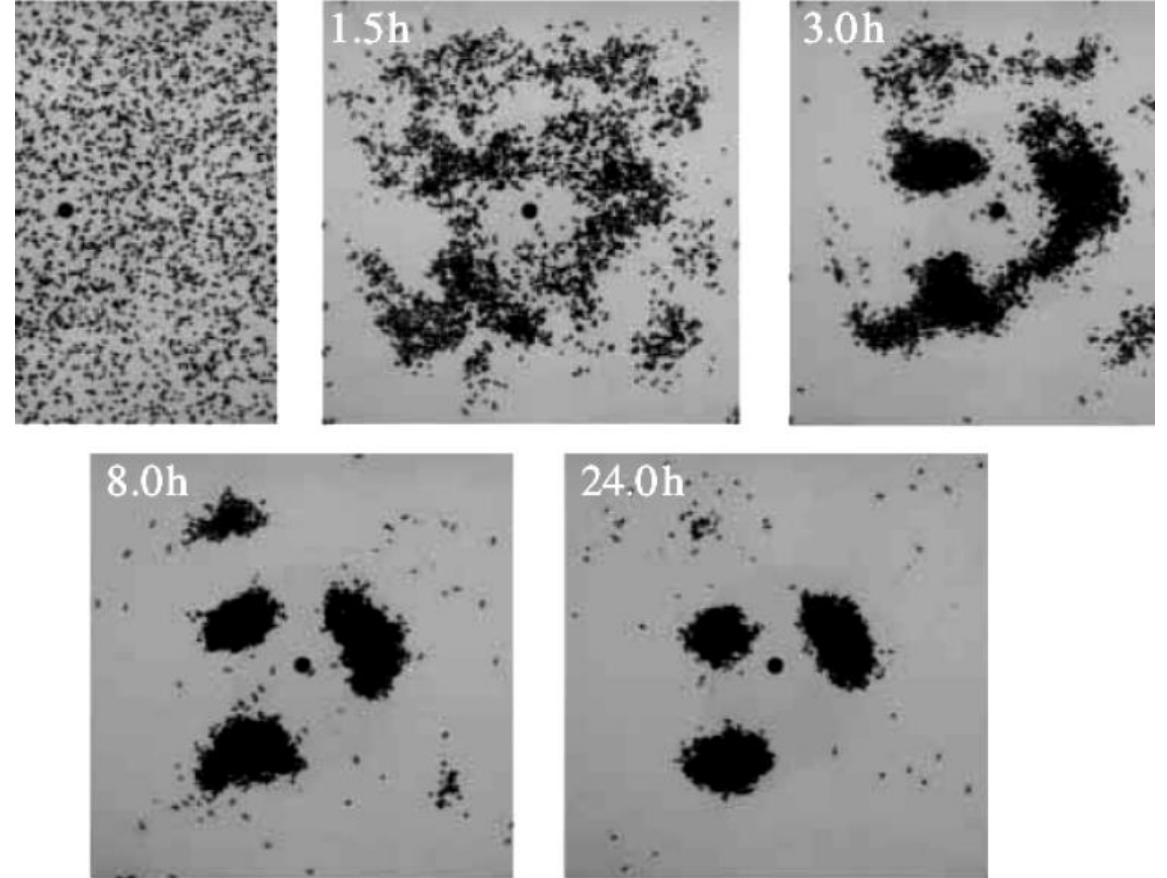
- **Induction:** inferring from particular data a general theory
- **Deduction:** reasoning from first principles to a general theory

Third Way

- **Generative:** using first principles to generate a particular set of data that can create a general theory

Ant Corpse Piles

- How does it work?
- Is it swarm intelligence?
- What is the simplest model able to explain the process?



Jost *et al.*, J. R. Soc. Interface, 2007

Agent-Based Models (ABMs)

Modeling the basic entities as individuals and observe the global *emergent* behavior.

The Traffic Basic Model

Basic Components of ABM

- Agents
- Environment
- Interactions



Agents

Agents are the fundamental entities of ABM

Concept introduced in the Artificial Intelligence field

Autonomous and decentralized

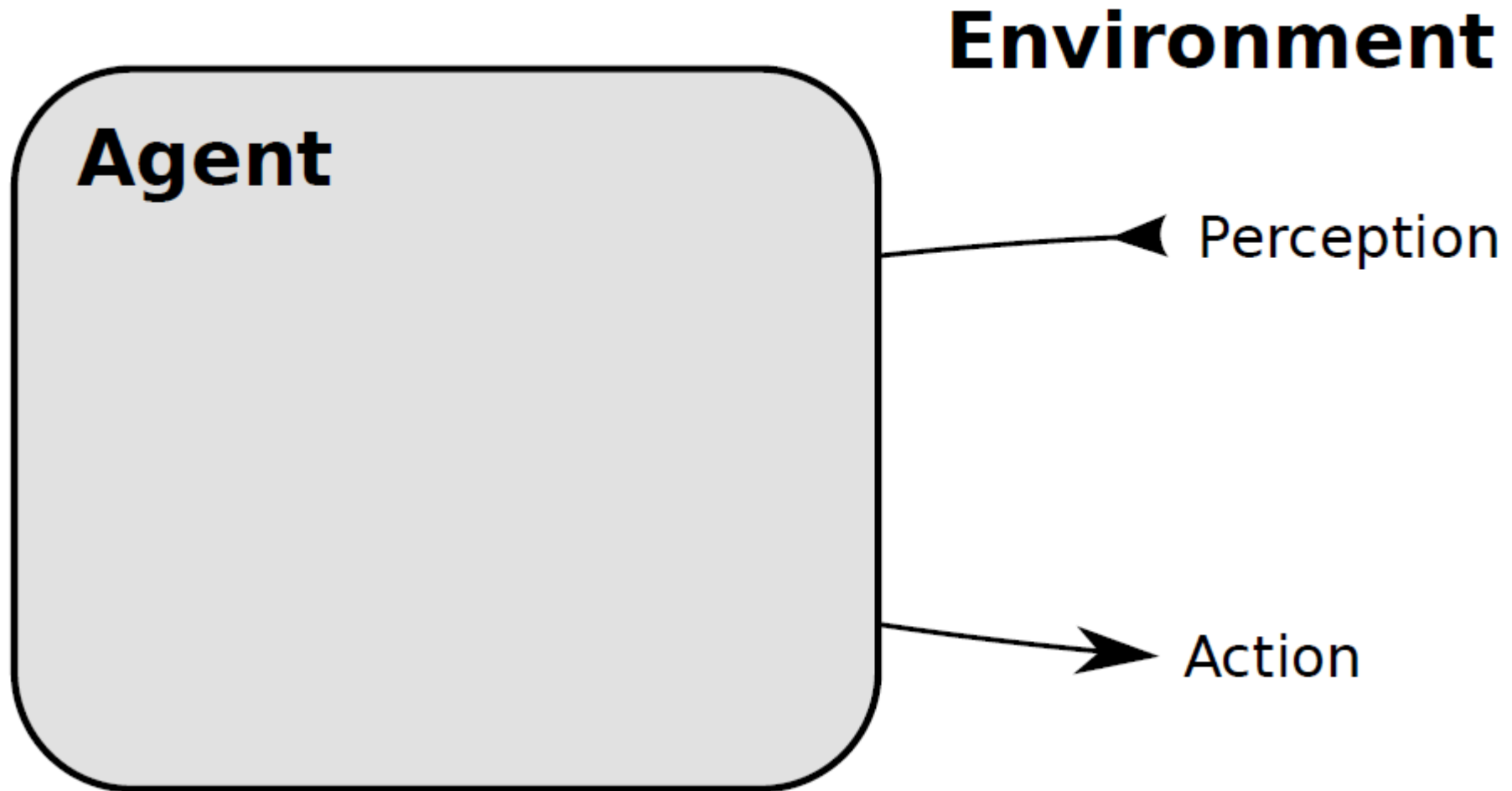
Interact with an environment



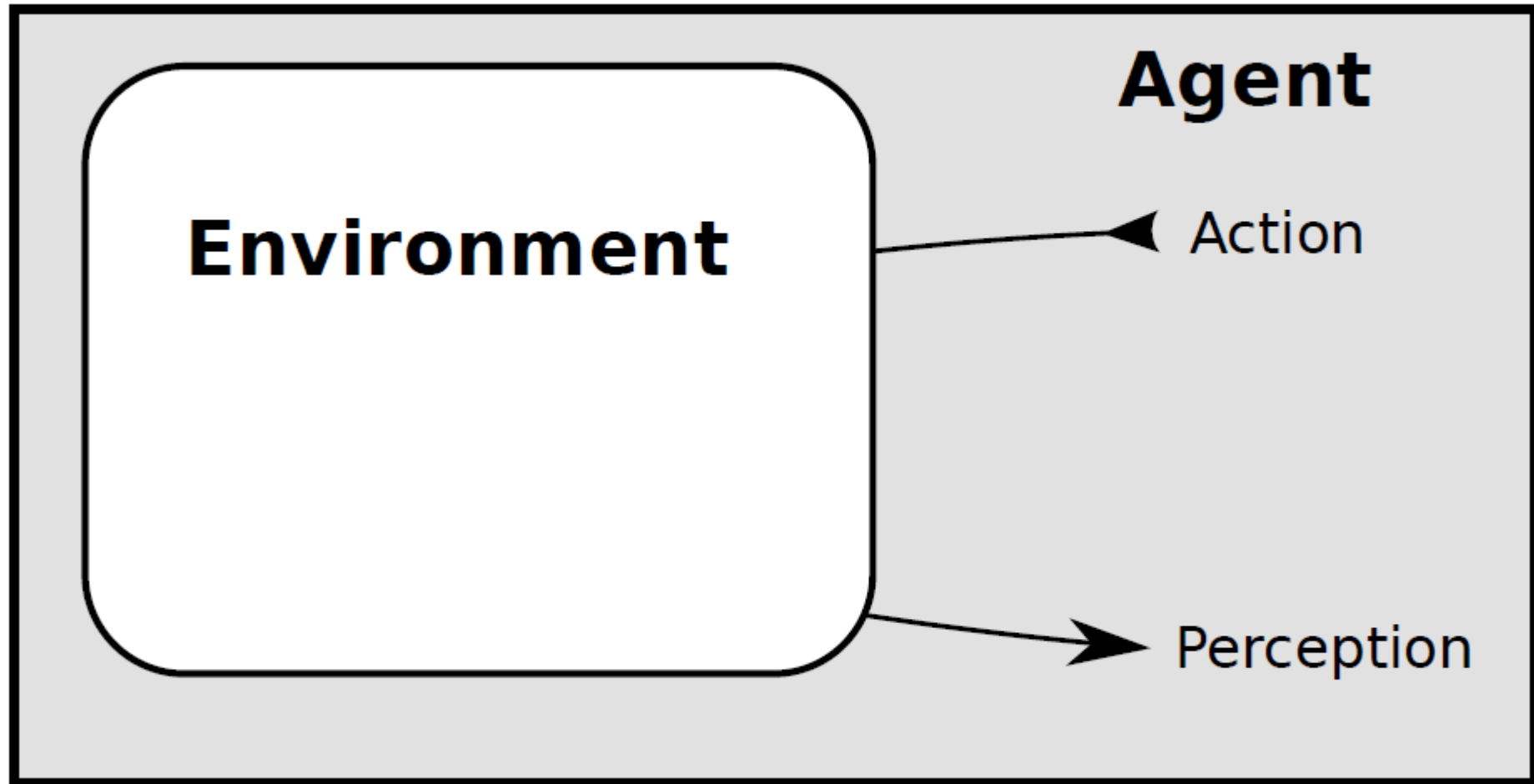
Agent Schools

- **Artificial intelligence**
 - Agents as autonomous entities solving problems
- **Multi-agent systems**
 - Distributed control of systems
- **Agent-based modeling (and simulation)**
 - Simulating (real world) phenomena

Agents



From the Agent Point of View



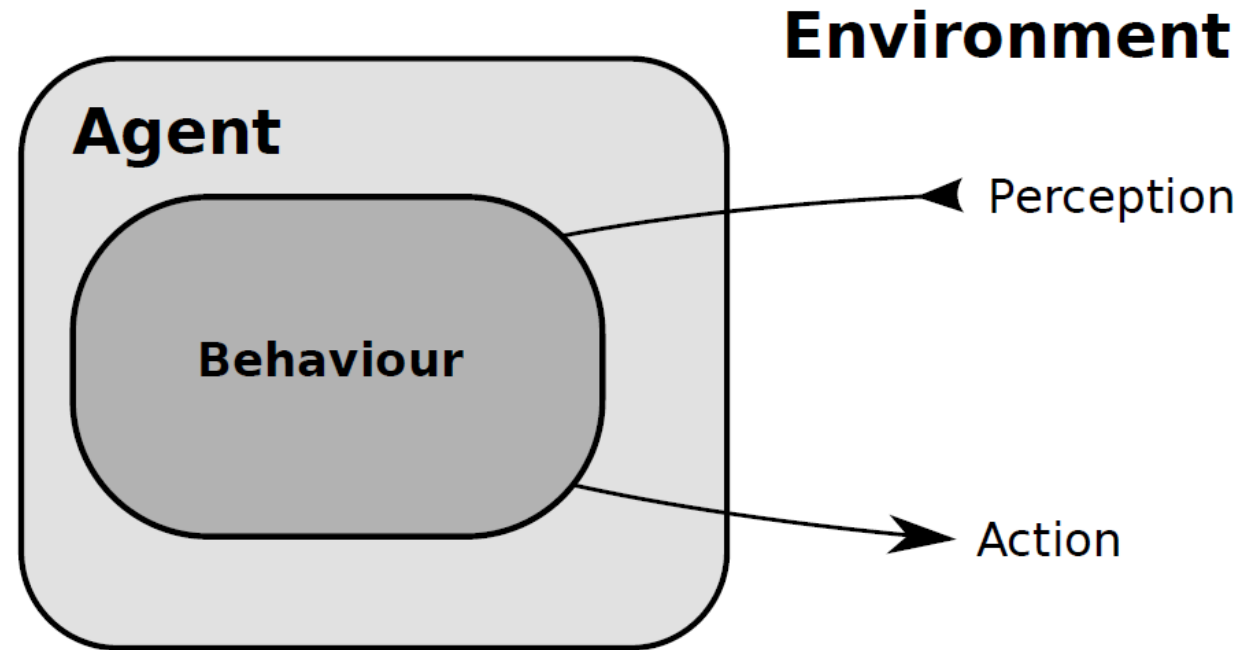
Simple Reflex Agent

Behavior: how the agent will react to the environment *perception*.

- Usually rule-based (Finite State Machine)

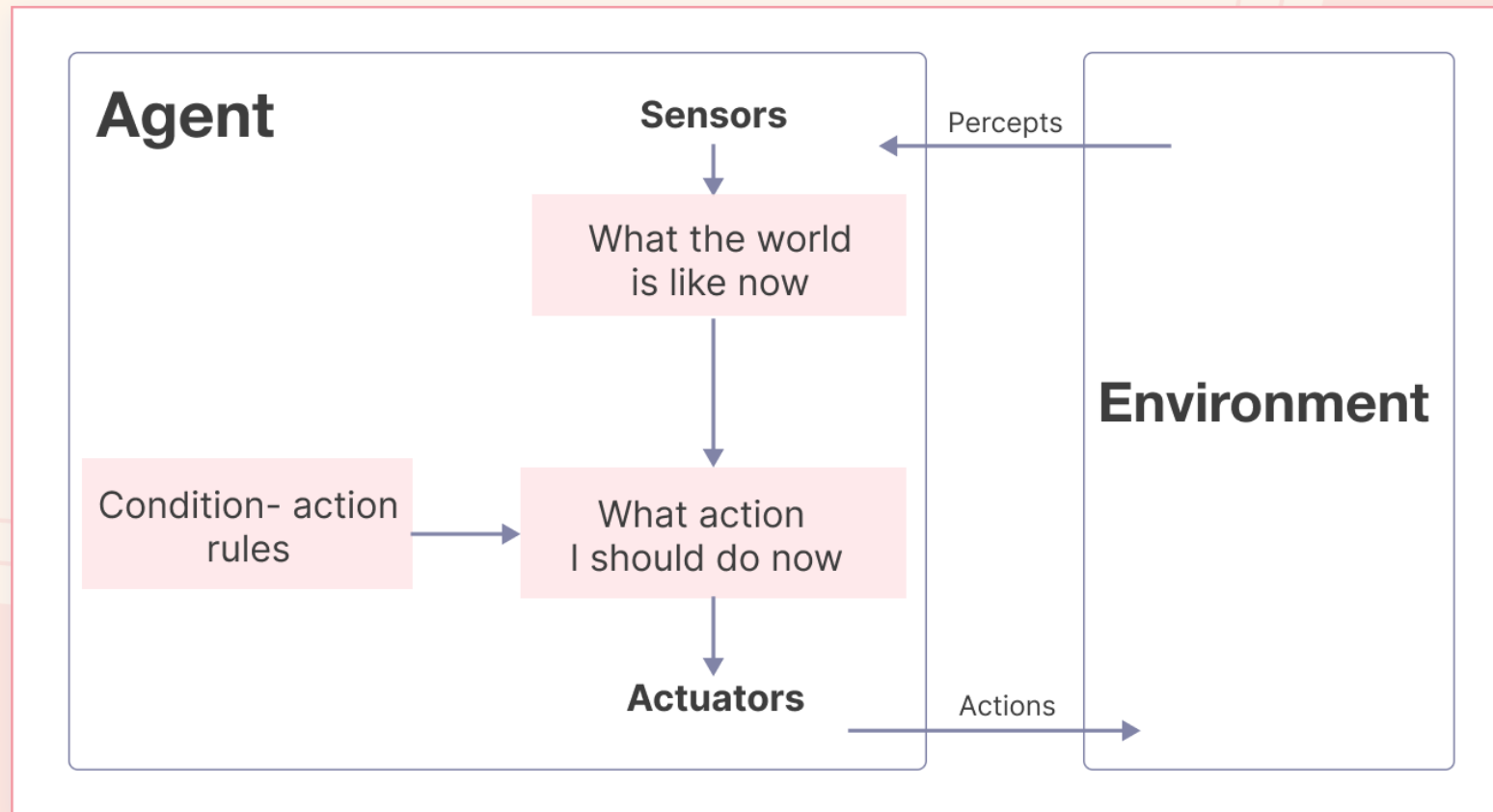
Perception → *Action*

- May be stochastic
- Perception/Knowledge of environment is limited
- The *action* may affect the environment

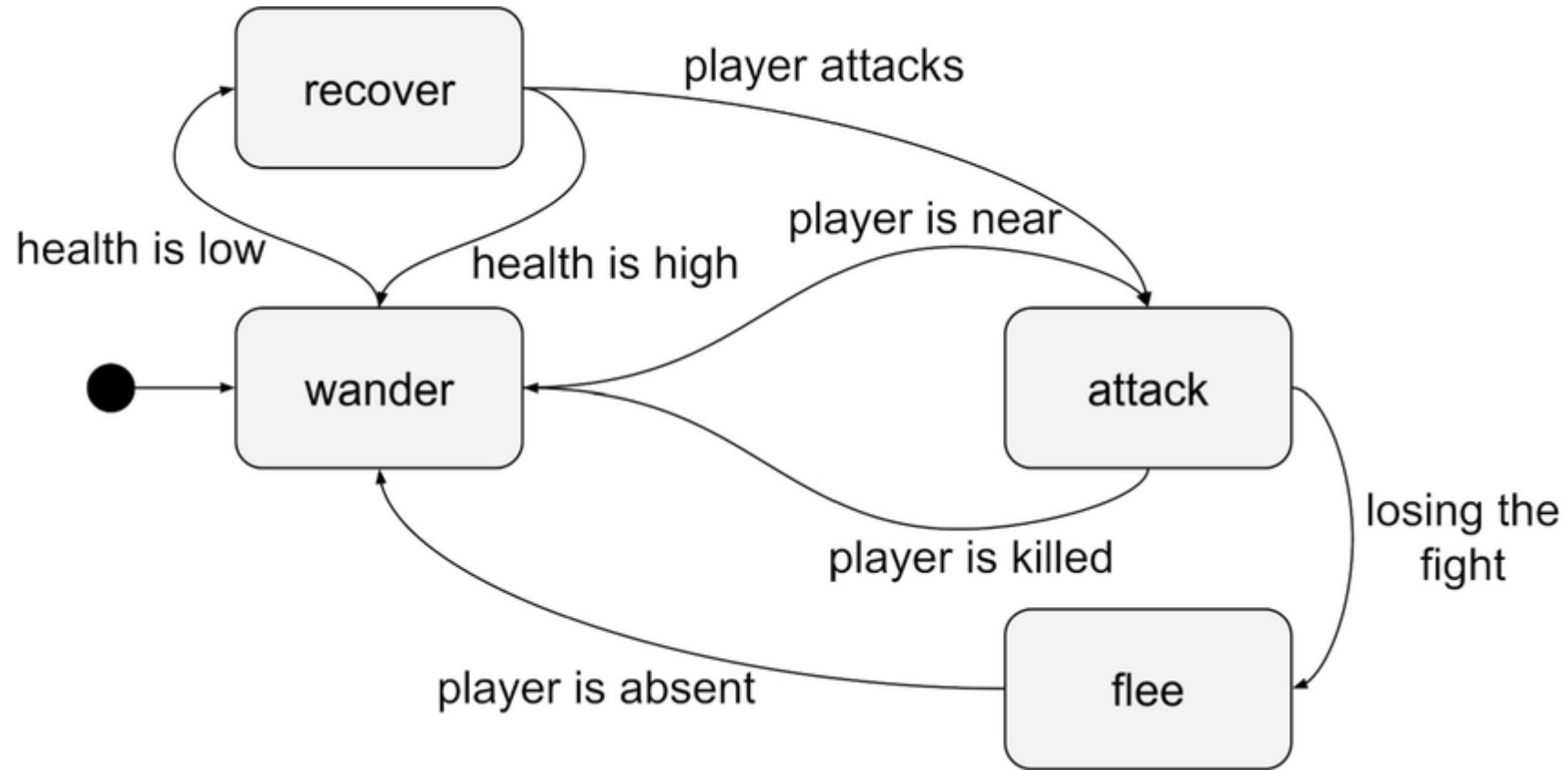


Simple Reflex Agents

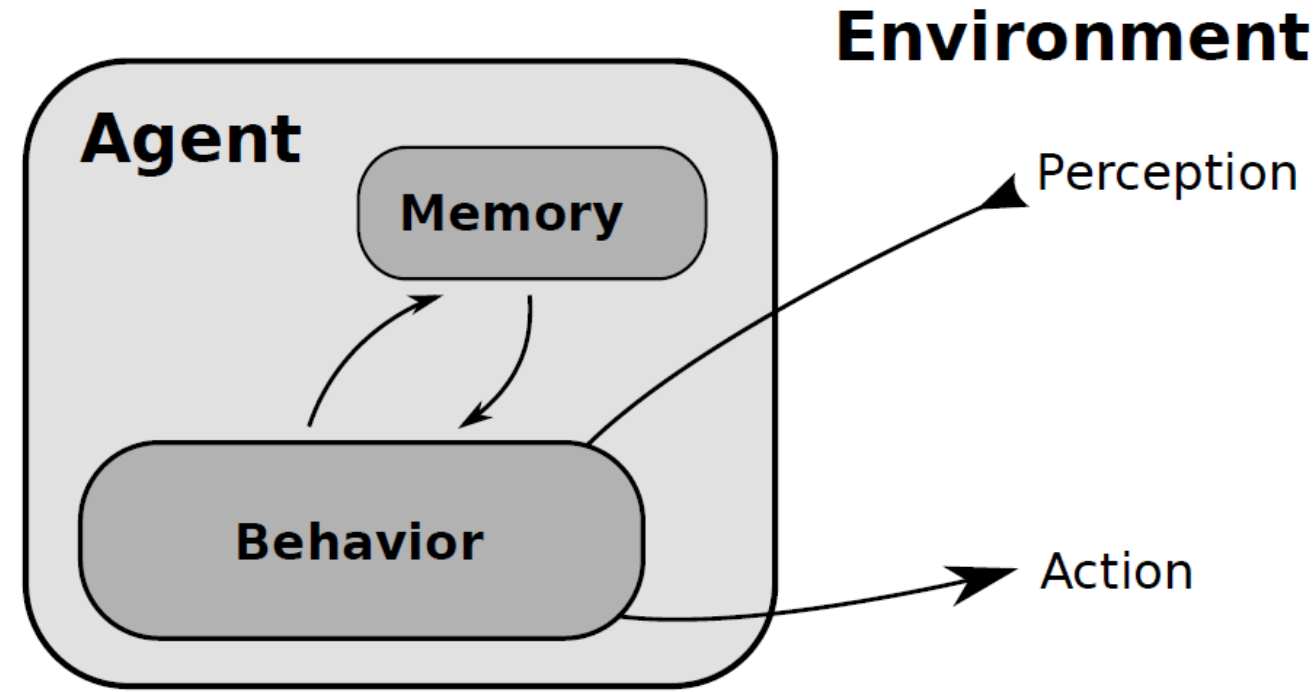
Simple Reflex Agent



An FSM for an NPC



Intelligent Agent



The agent has a state, which can be as simple as a boolean or as complex as it needs to be

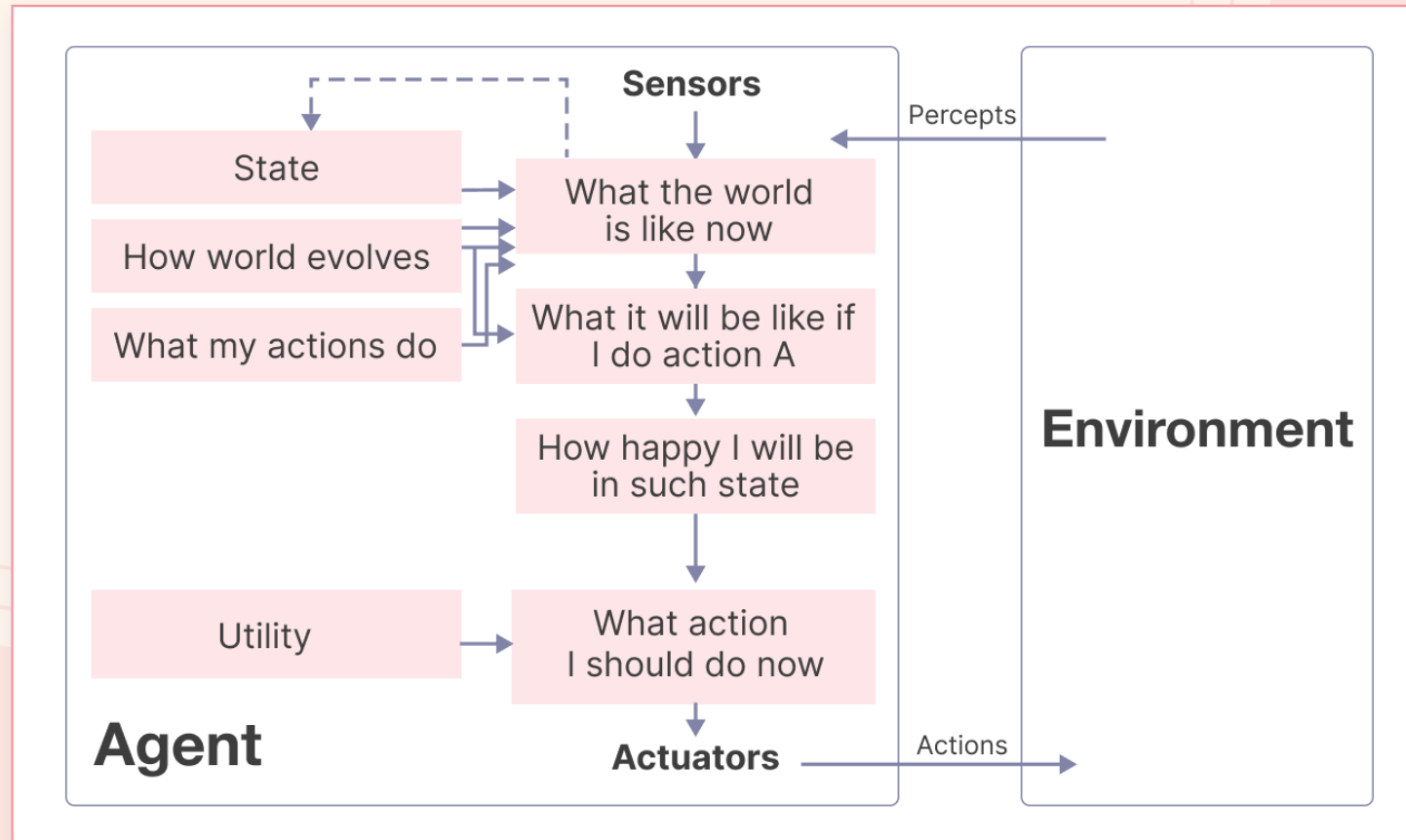
Behavior function:

$$\textit{Perception} \times \textit{State} \rightarrow \textit{Action} \times \textit{State}$$

- The state is a kind of memory of past perceptions/actions
- The behavior depends on memory
- Hence, the agent is capable of learning

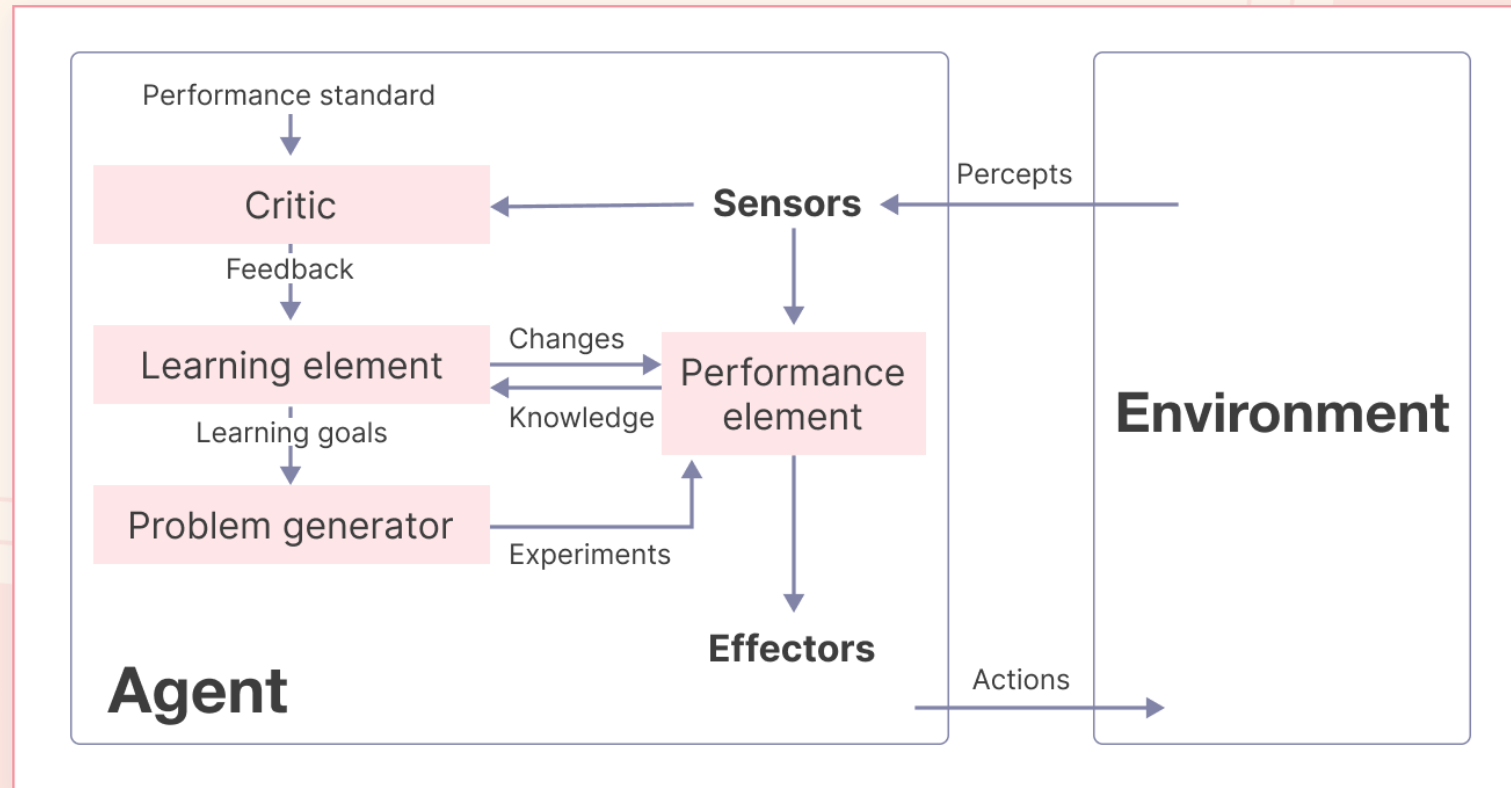
Utility-Based Agents

Utility-based Agent

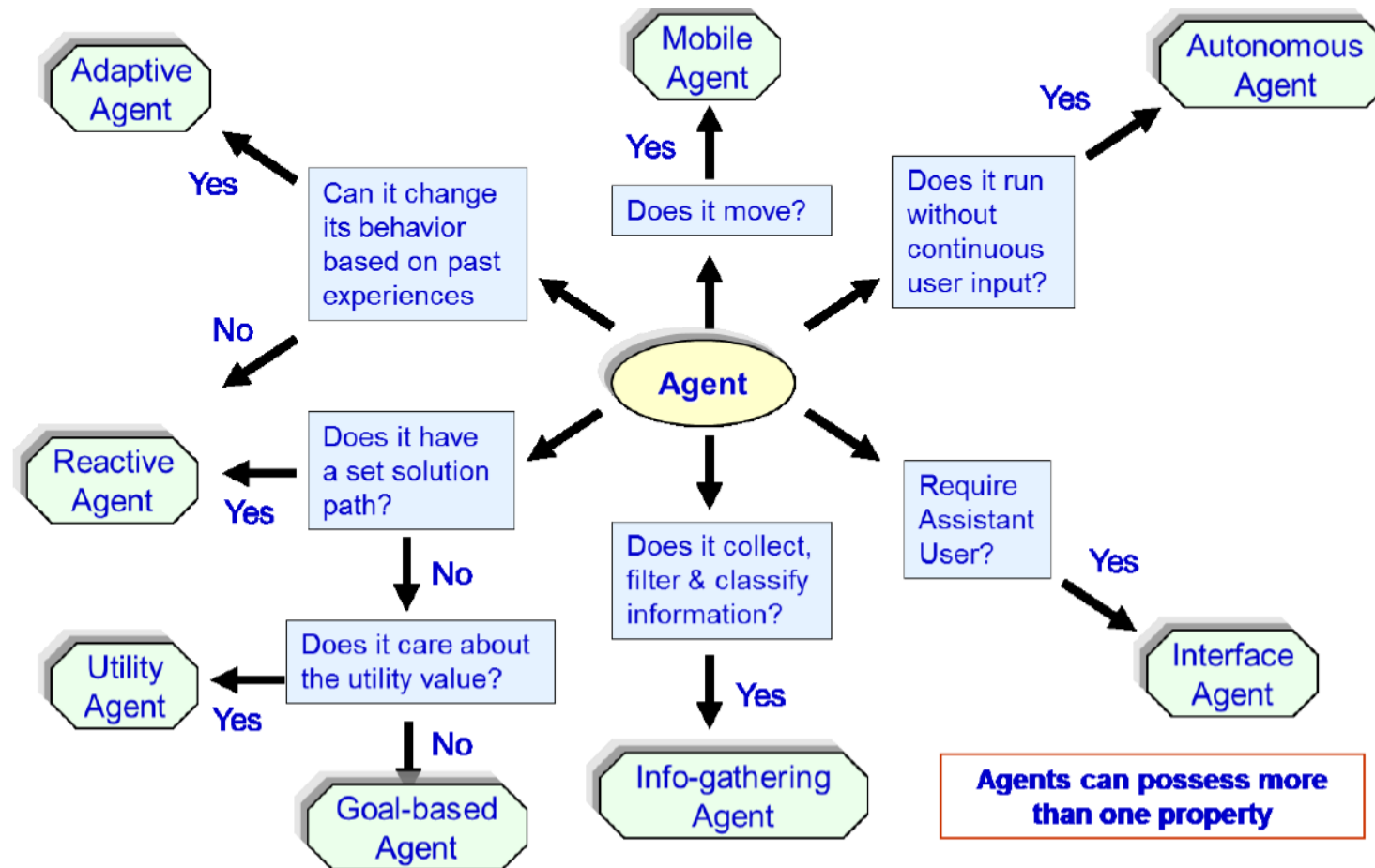


Learning Agents

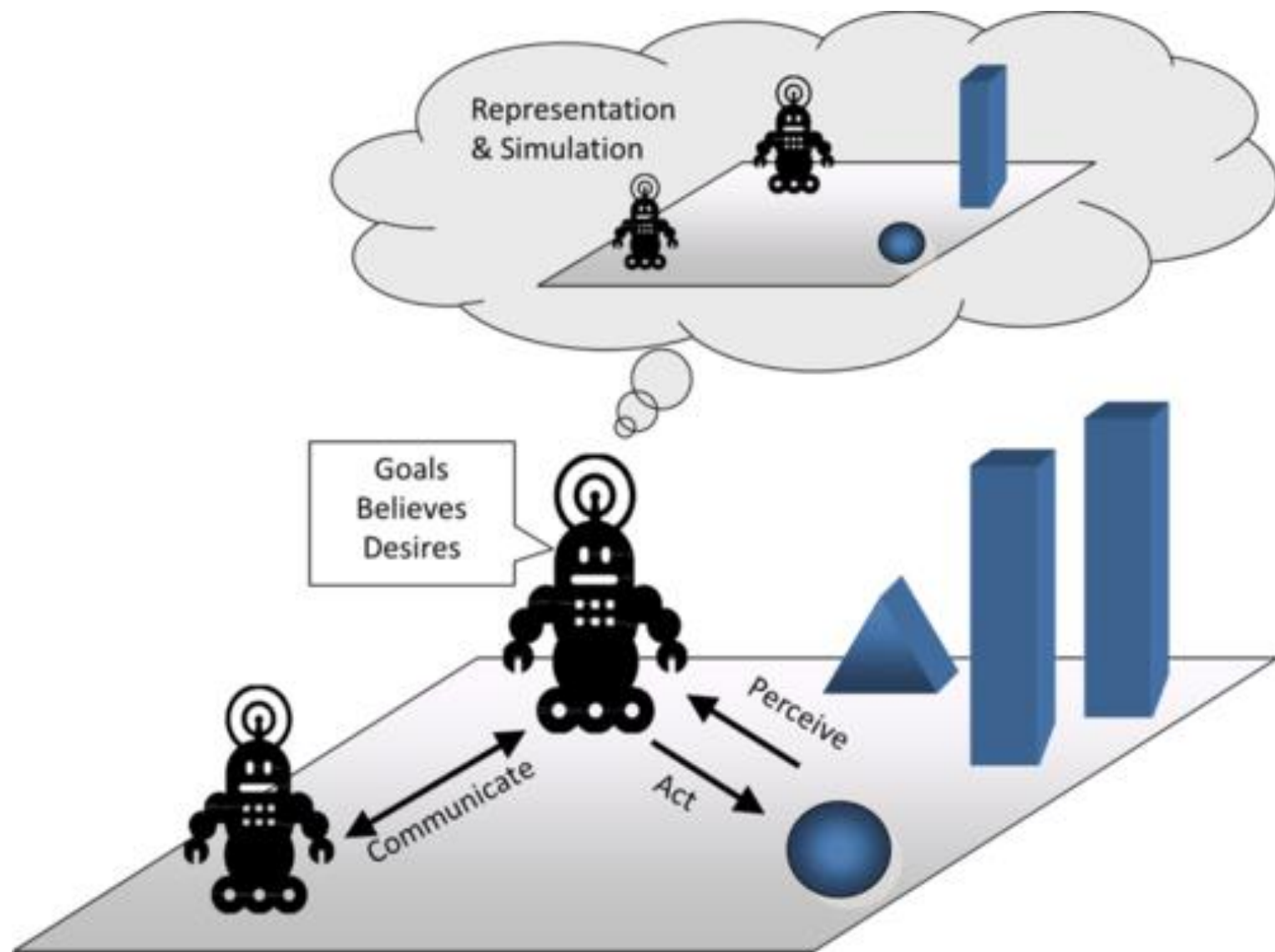
Learning Agent



Agent Types

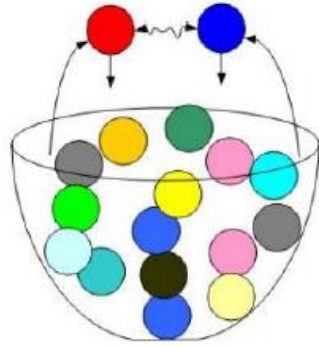


Environments



Some Types of Environments (Combinations and Variations are Possible)

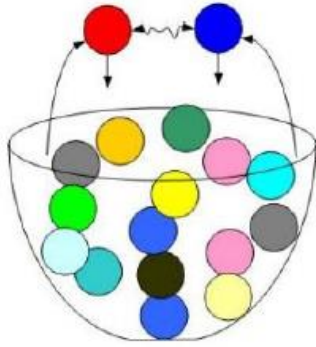
Simple Genetic Alg



(a) "Soup" Model (Aspatial)

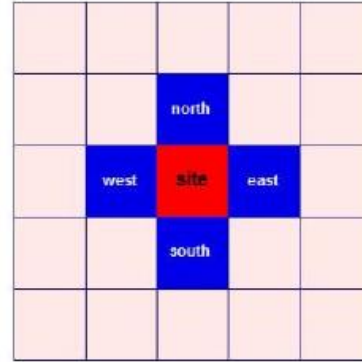
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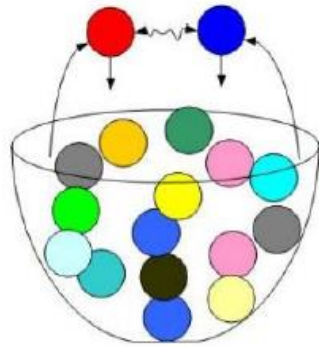
Lattice Gas Automaton



(b) Cellular Automata (von Neumann)

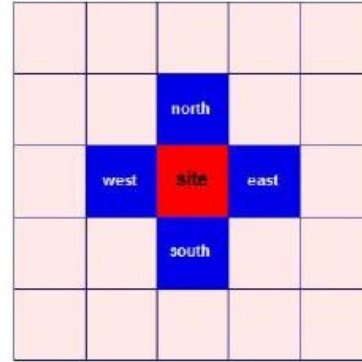
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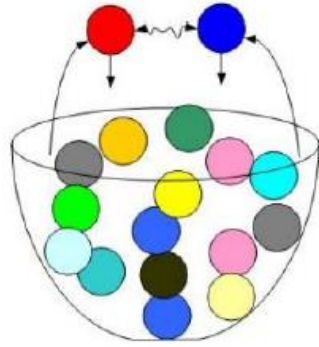
Flocking



(c) Euclidean Space (2-D)

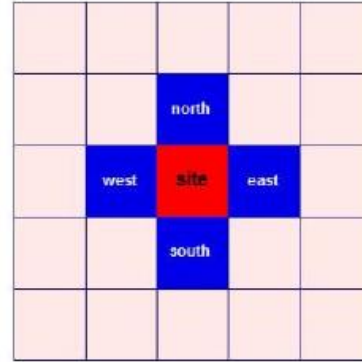
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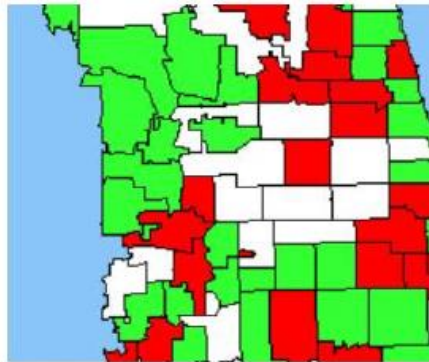


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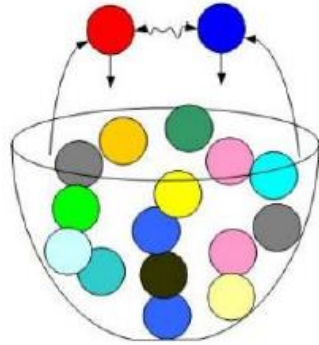


(d) Geographic Information System (GIS)

Grand Canyon Model

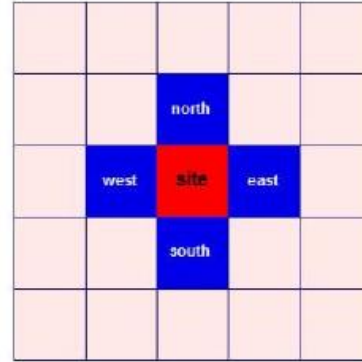
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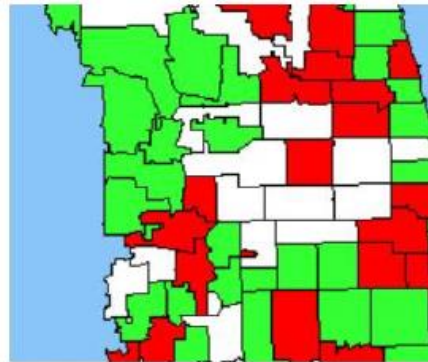


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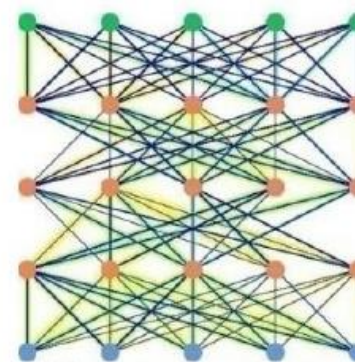


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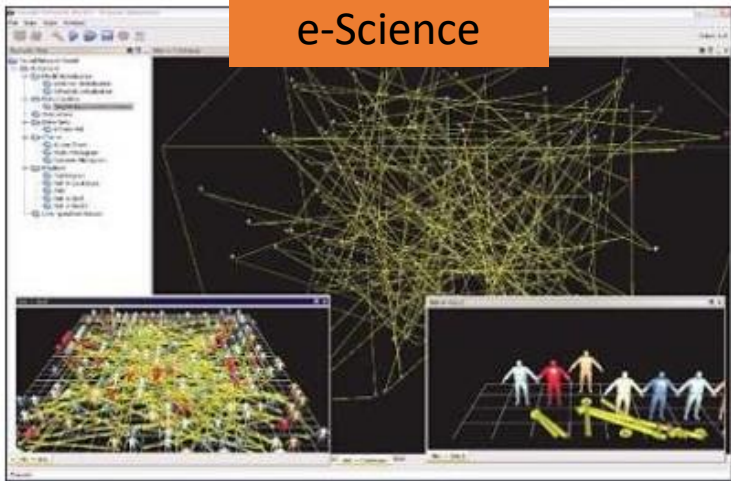
Grand Canyon Model



(e) Network topology

Virus on a Network

Four Types of Problems based on Agent/Environment



e-Science

Artificial agents, artificial environment



Behavioral Experiments

Natural agents, artificial environment



Engineering Applications

Artificial agents, natural environment

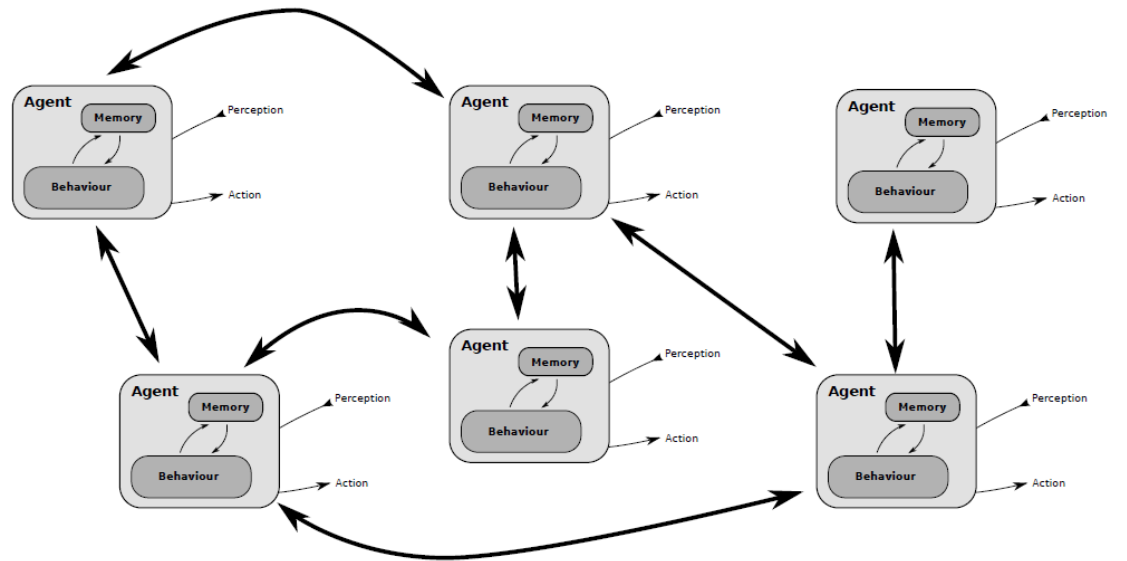


Descriptive Model

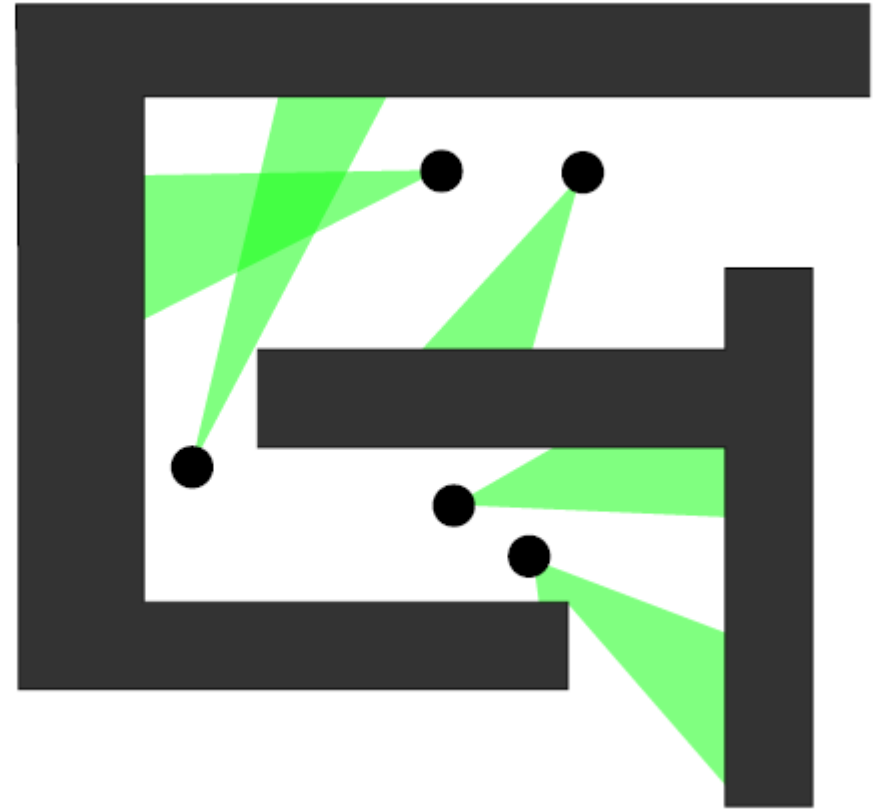
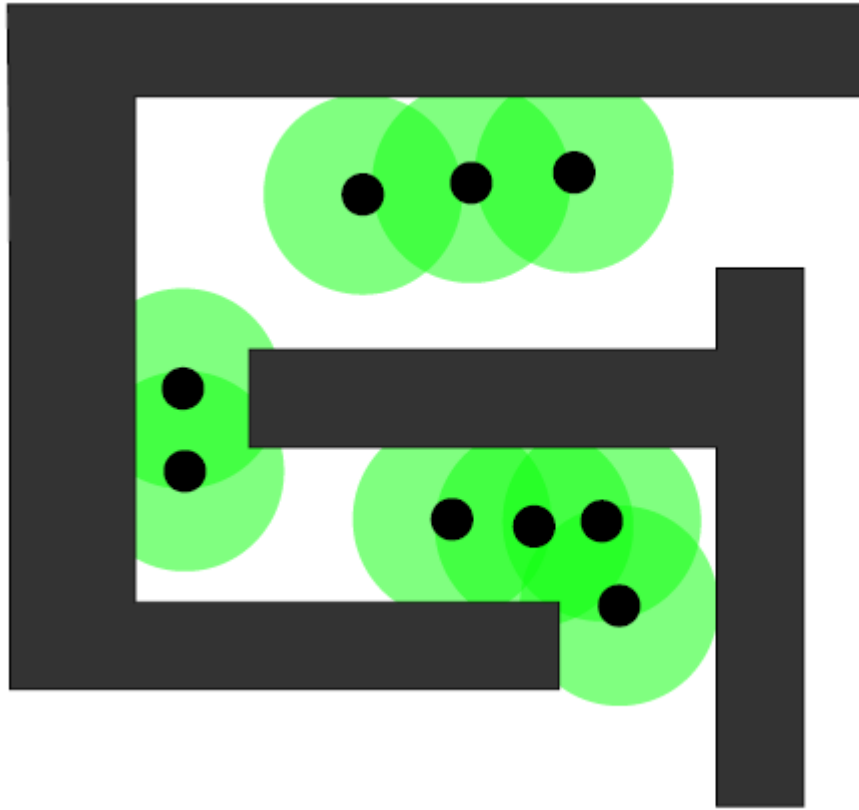
Natural Agents, natural environment

Interactions

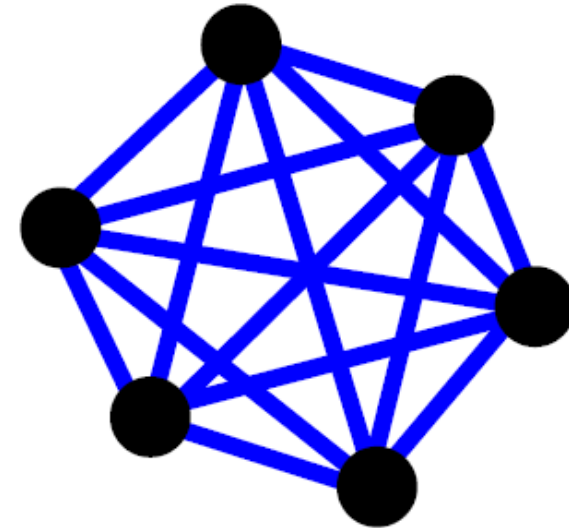
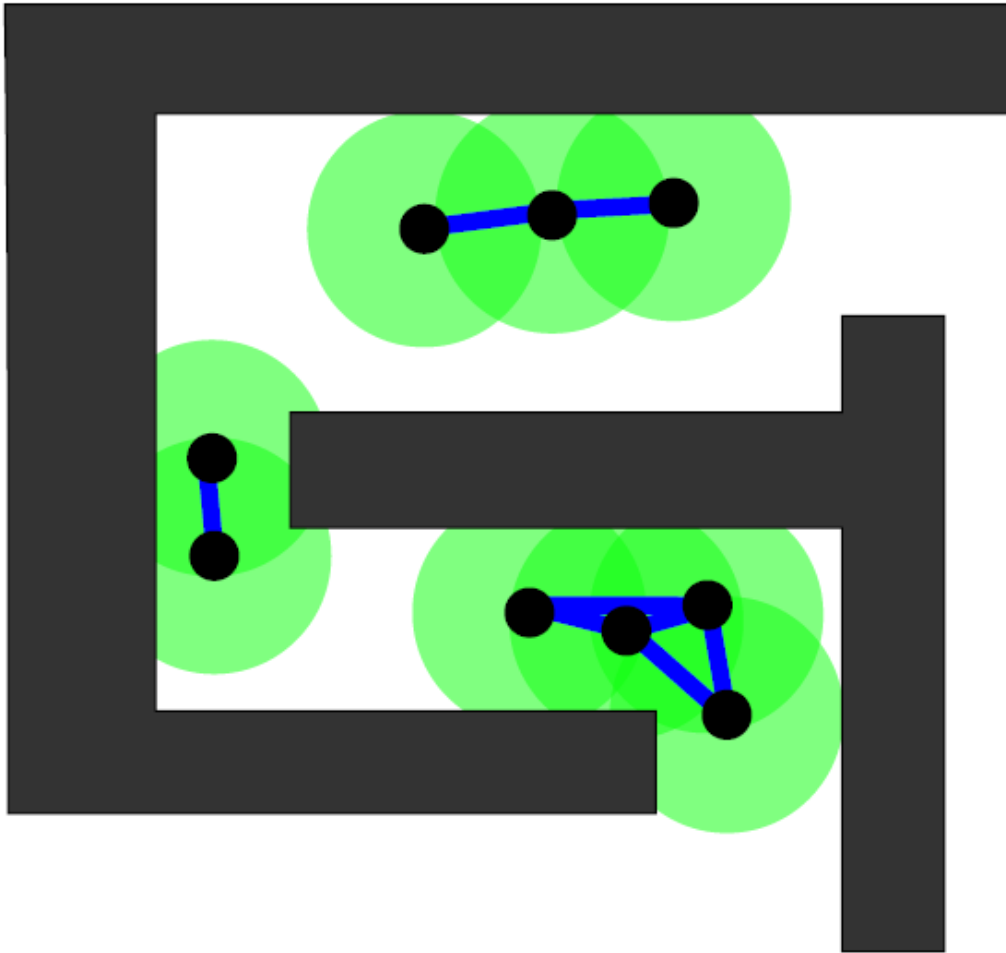
Environment



Environment Awareness



Interaction Topology



Interaction Types

- Agent – Self (e.g., reproduction)
- Environment – Self (e.g., grass)
- Agent – Agent (e.g., wolf-sheep)
- Agent – Environment (e.g., sheep-grass)
- Environment – Environment (e.g., diffusion in ants)

When to Use ABM?

Medium Numbers (Mesoscopic)

Too few agents and the “simple” may be too simple

- Game theory and ethnography work well

Too many agents and “means” may describe the system well

- Mean-field approaches and statistical descriptions

The key is that the number of agents that can affect the outcome of the system be a **medium number**.

Heterogeneity

- Agents can be as heterogeneous as they need to be
- Many other approaches assume homogeneity over individuals

Complex but Local Interactions

ABM can model complex interactions

- History dependent
- Property dependent

The assumption is that these are local

- No global knowledge

Rich Environments

The environment the agents interact in can be extremely rich

- Social Networks
- Geographical Systems
- The environment can even have its own agent-like rules
- ...

Time

Almost all agent-based models feature time

- ABM is a model of process
- Nearly necessary
- There are exceptions
 - Solving complex equilibrium problems

Adaptation

- Adaptation is when an agent's actions are contingent on their past history
- An agent may take different actions depending on its own past experience
- Very few modeling approaches besides ABM feature adaptive individuals

ABM vs EBM (Equation-Based Modeling)

- Many EBMs make the assumption of **homogeneity**
- EBMs are **often continuous and not discrete**
 - The nano-wolf problem (Wilson, 1998)
- EBMs require **aggregate knowledge** in many cases
- Ontology of EBMs is at a **global level**
- EBMs **do not provide local detail**
- EBMs are Top-Down, ABMs are **Bottom-Up**
- EBMs are **generalizable**, but restricted
- ABM can be built from analytical models, and can **complement** EBMs

ABM and Statistical Modeling

- Hard to link to first principles and behavioral theory
- Need to have the right kind of data
- ABM can complement by building from first principles to statistical results

ABM vs Lab Experiments

- Lab experiments can generate theory
- Lab experiments are rarely scaled up
- ABM can be created from lab experiments
 - ABM can explore macro-implications of lab experiments
 - ABM can generate new hypotheses
 - ABM can determine sensitivity of results
 - ABM can compare generative principles

Limitations

High Computational Cost

- Benefit of more insight and data to intermediate stages

Many Free Parameters

- Simply exposing parameters that other models assume

May Require Individual-Level Behavioral Knowledge

- Provides better insight

Why is ABM Resisted?

- Lack of Education about Complex Systems
- The Drunk, The Keys and The Streetlight
 - People want to search for solutions where it is easy
- Centralized and Deterministic Mindset
 - People expect their to be a central leader
 - People expect that everything happens for a “cause” and negate the possibility of chance

Uses of ABM

- Description (a simplification of a system)
- Explanation (underlying phenomena that control a system)
- Experimentation (make interventions)
- Analogy (boids to swarm of drones)

- Education (easy to understand, explore, and experiment)
- Touchstone (turns complex systems to simple rules)
- Thought Experiments (think of anything and experiment)
- Prediction (future scenarios – Very careful here...)

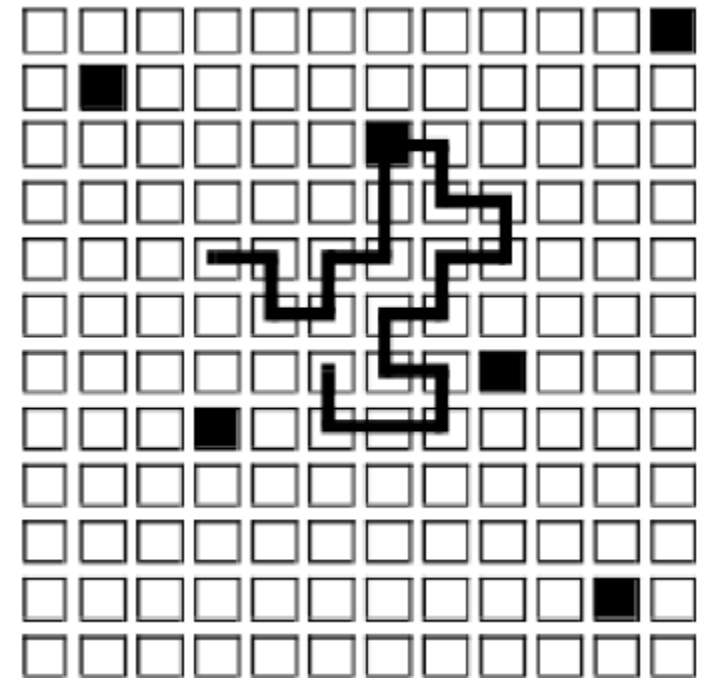


Back to the Ants

Termites Mo

Deneubourg's Model (1991)

- Ants on a regular grid, with 4 directions (von Neuman neighborhood)
- Random walk, can walk over a corpse
- Sequential (asynchronous) updating scheme



Ant Behavior

- With probability P_p , the workers pick up a corpse if it is isolated or in a small cluster
- With probability P_d , the workers deposit a corpse in large cluster of dead bodies

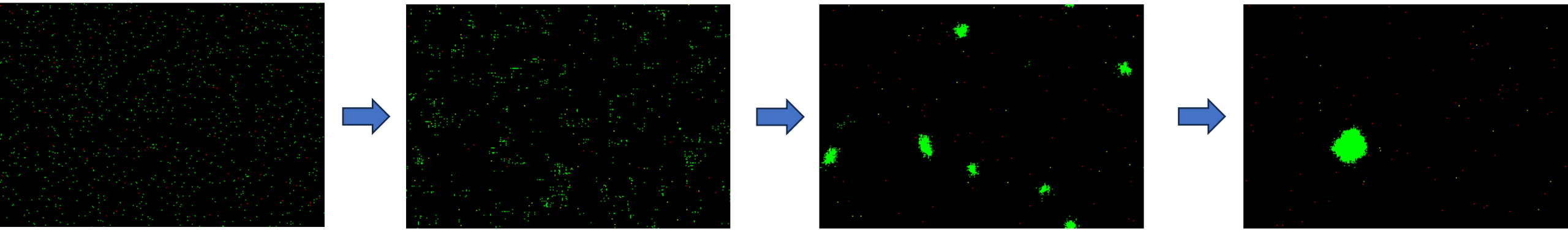
How does the ant evaluate the cluster size?

- Each ant has a memory M of size n :
- The memory locations indicate the state of the cells visited by the ant during the last n steps: $M(i) = 1$ if there was a corpse at time $t - i$, 0 otherwise

$$f = \sum_{i=1}^n M(i)$$
$$P_p = \left(\frac{k_1}{k_1 + f} \right)^2$$
$$P_d = \left(\frac{f}{f + k_2} \right)^2$$

k_1 and k_2 are model parameters.

Simulation of Smart Ants

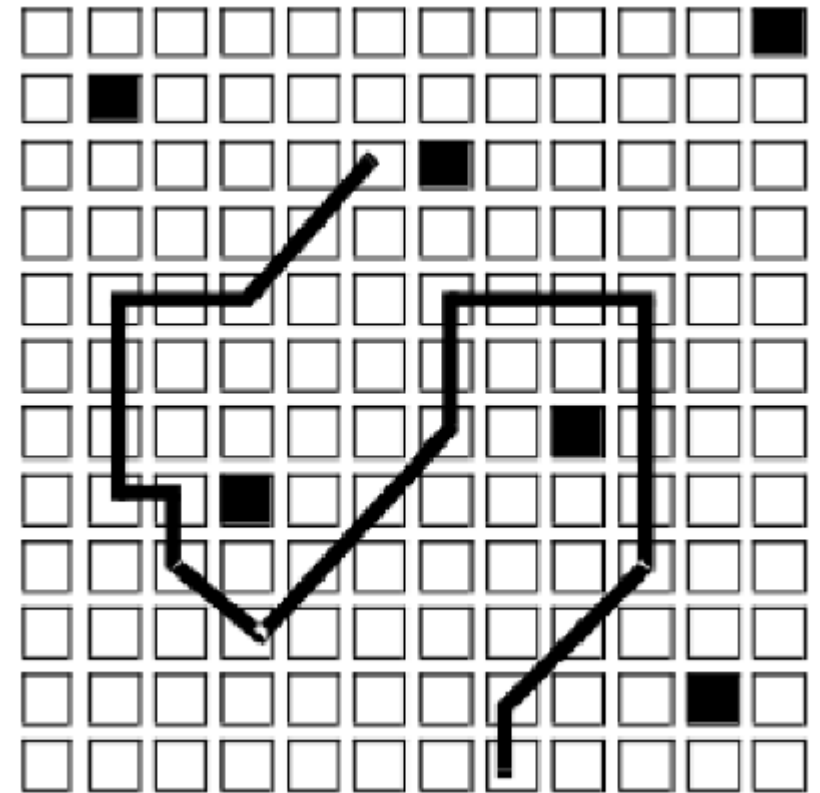


Deneubourg's model works well

- Basic mechanism is intuitive
- But it requires a lot of "intelligence" from ants
- What about dumber ants?

Unige Model (2000)

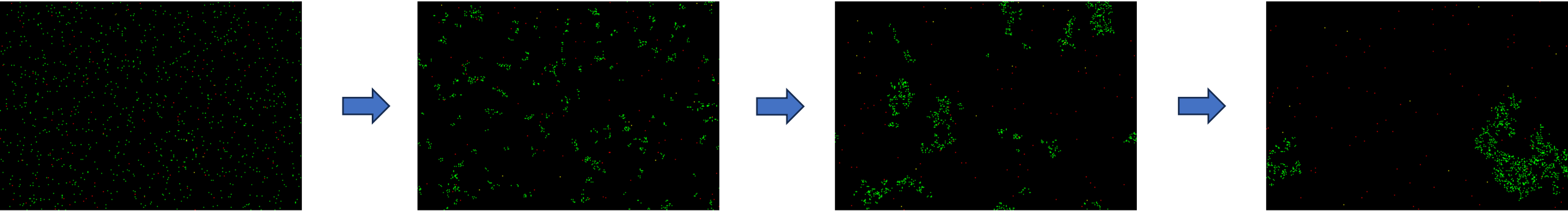
- Regular Grid, with 8 directions (Moore neighborhood)
- Random Walk with large diffusion constant
- Asynchronous updating



Behavior

- The ants avoids all obstacles:
 - ant corpses
 - other working ants
 - boundaries and walls
- An unloaded ant always picks a found corpse
- A loaded ant who finds another corpse always drops the carried corpse.

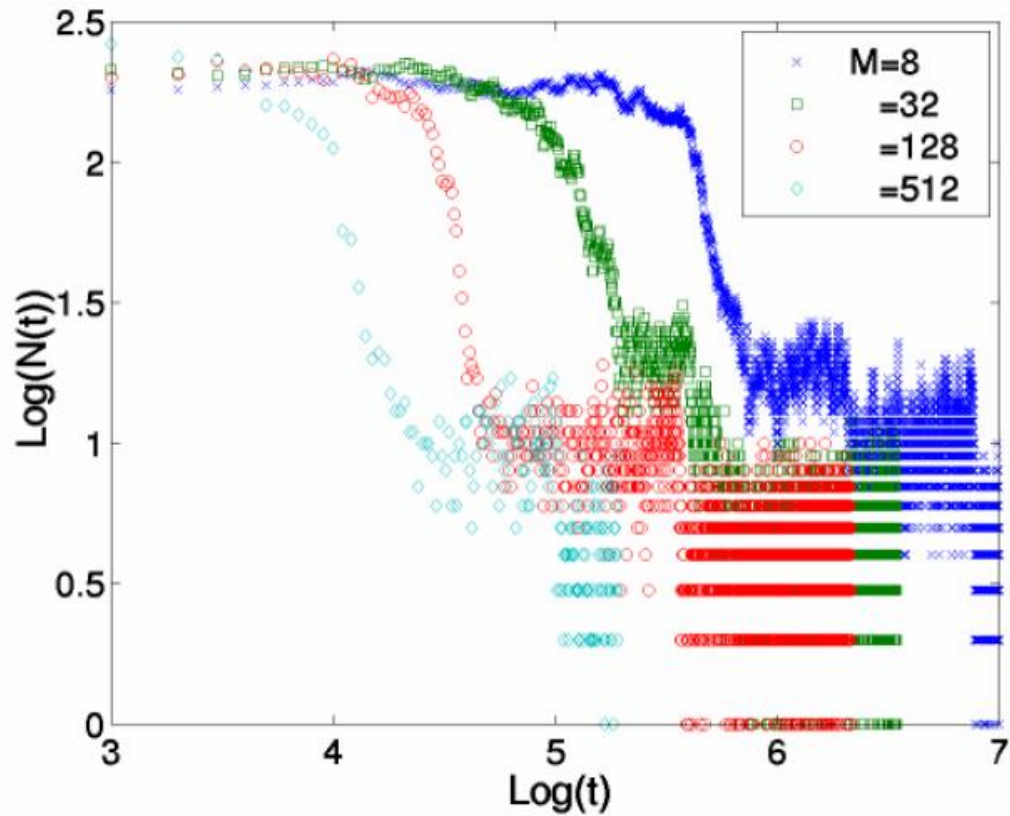
Simulation of Dumb Ants



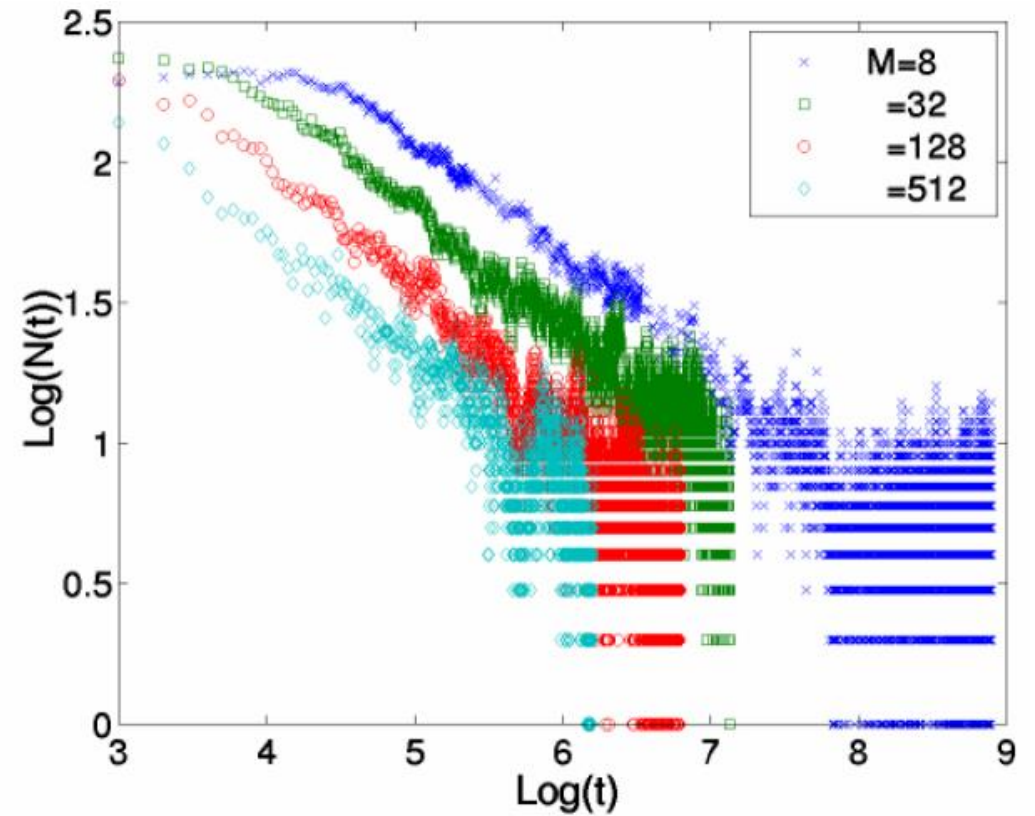
It works... but why?

- The probabilities to remove a corpse from a cluster, or to add a new corpse are the same.
- Ants make no difference between a large or a small cluster
- When a cluster is emptied it will never reappear.
- Due to fluctuations, all clusters but one will eventually reach a zero size

Quantitative Results

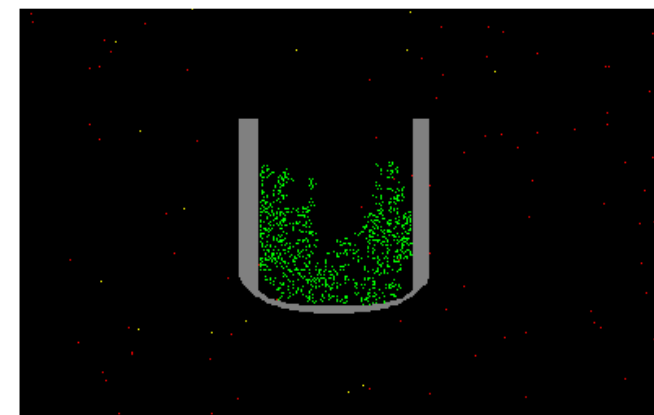
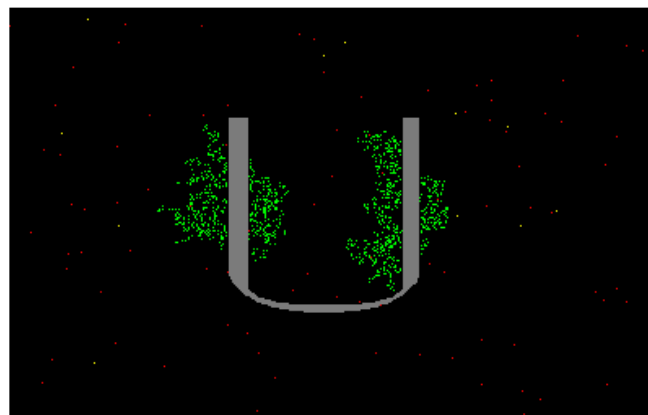
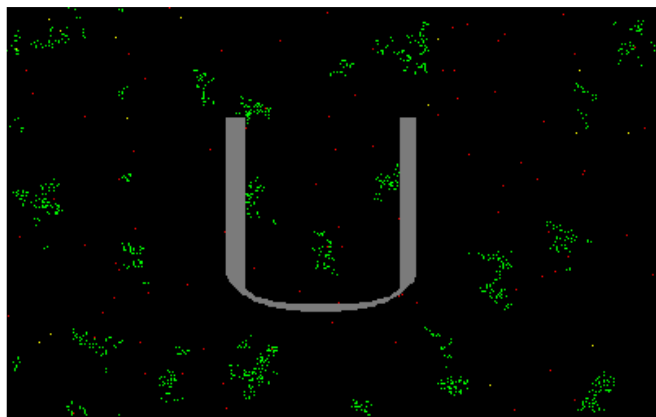


Deneubourg, with 8 directions



Unige

With Obstacle



Conclusions

- Ant corps pile construction can be explained by statistical fluctuations
- Yet, intelligence speeds up the process
 - In Deneubourg's model converges $\sim 10 \times$ faster (using better random walk).
- Not a collective effect, just a collaboration with a linear speedup
 - One single ant would make it, but slower
 - In both models: not a collective behavior, $N(t) = f(Mt)$



A Sketchbook for Ethics in Agent-Based Modelling

Slides taken from Andy Evans



Crime Modeling

Agent-based modelling of crime (burglary) at the city scale (Leeds in UK).

Ongoing collaboration with local police/government crime prevention partnership.

Model process

Inputs

Real offender homes
(postcodes)

Victims from census
(microsimulated ~100
household scale)

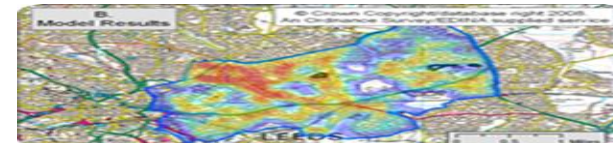
Behaviour

Offender behaviour model
(drug use, sleep, socialising,
work, knowledge of city)

Victim daily routines
(sleep, socialising, work)

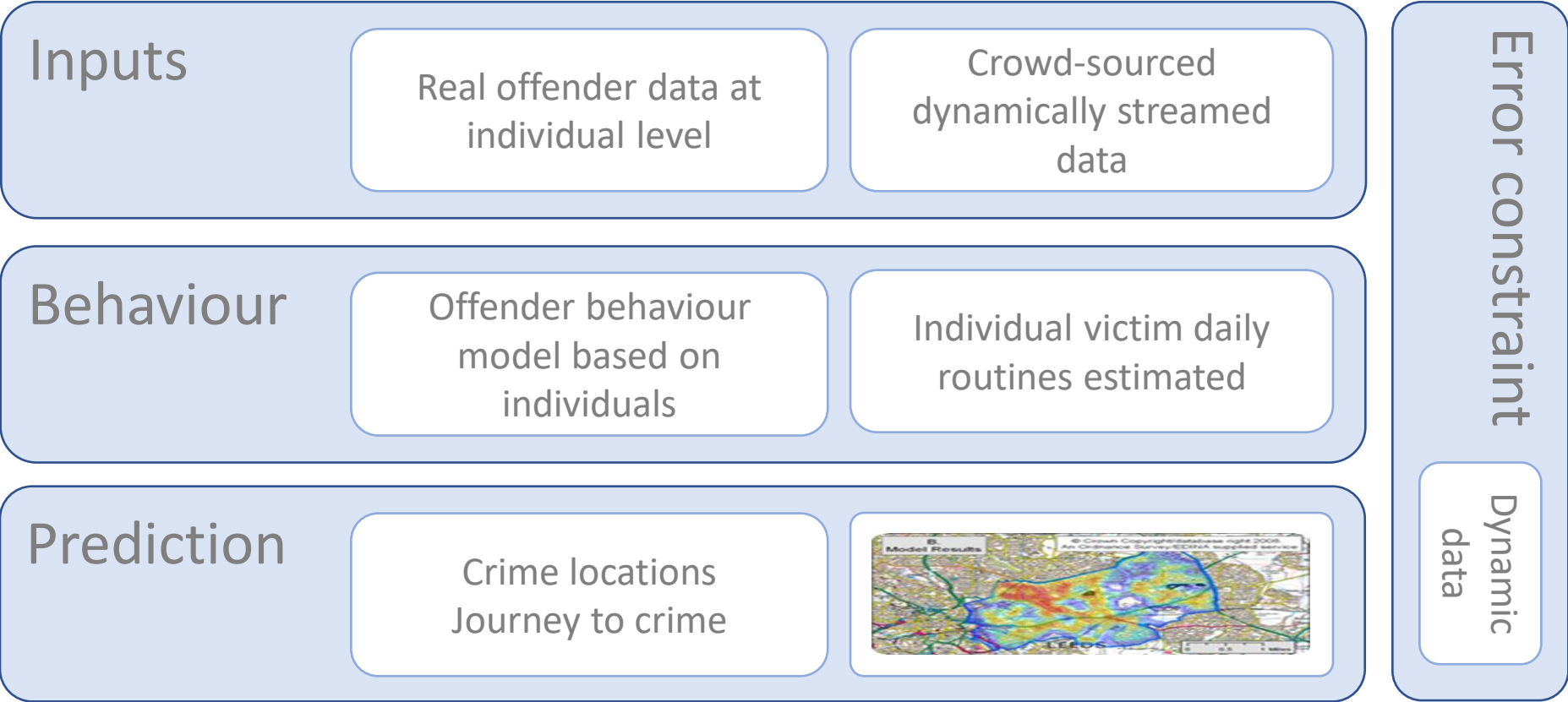
Prediction

Crime locations
Journey to crime



This is a likely model for all agent-based (and other) socio-economic studies, not just crime.

Near future



Ethics

Inputs

Personal data

Ethics well understood

Behaviour

Validation of personal
behaviour

Ethics poorly understood

Prediction

Predicted personal behaviour

Ethics rarely considered

Individuals

Crime prediction: Burglar committed to crime. (Think of Minority Report)

Sales opportunity prediction: Pregnant woman who is trying to hide it from an abusive family.

Input data

Data volunteered for another purpose / to secure other services

Data volunteered for the purpose

Data volunteered for purpose which is then perverted

Data not volunteered

Data extracted by force

Data

Are there differences between these?

Data volunteered for another purpose / to secure other services

Data volunteered for the purpose

Data volunteered for purpose which is then perverted

Unanticipated derived data



Difference depends in part on legitimacy of purpose.
Social good
Is commerce a sufficient social good?

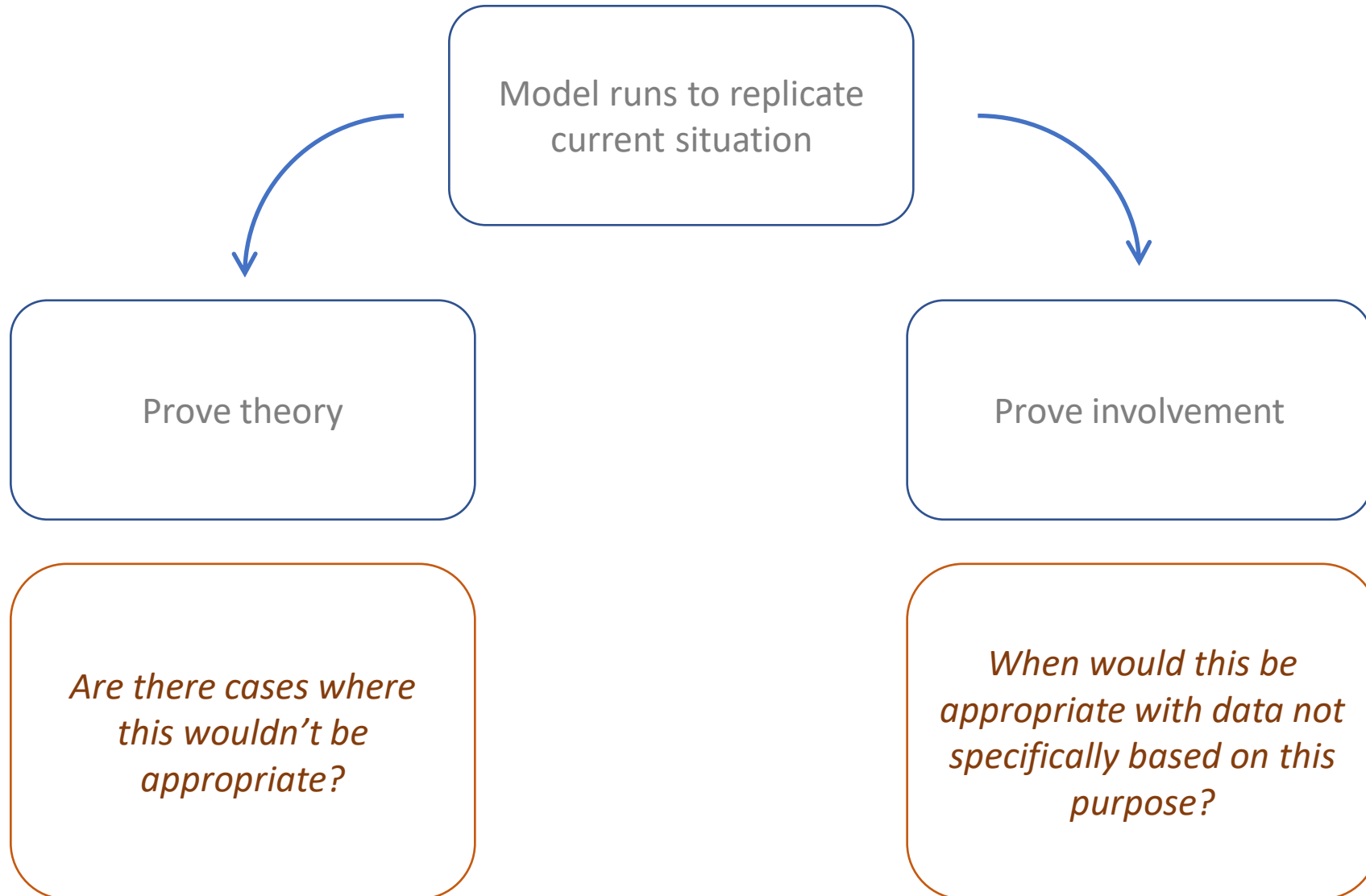
Levels



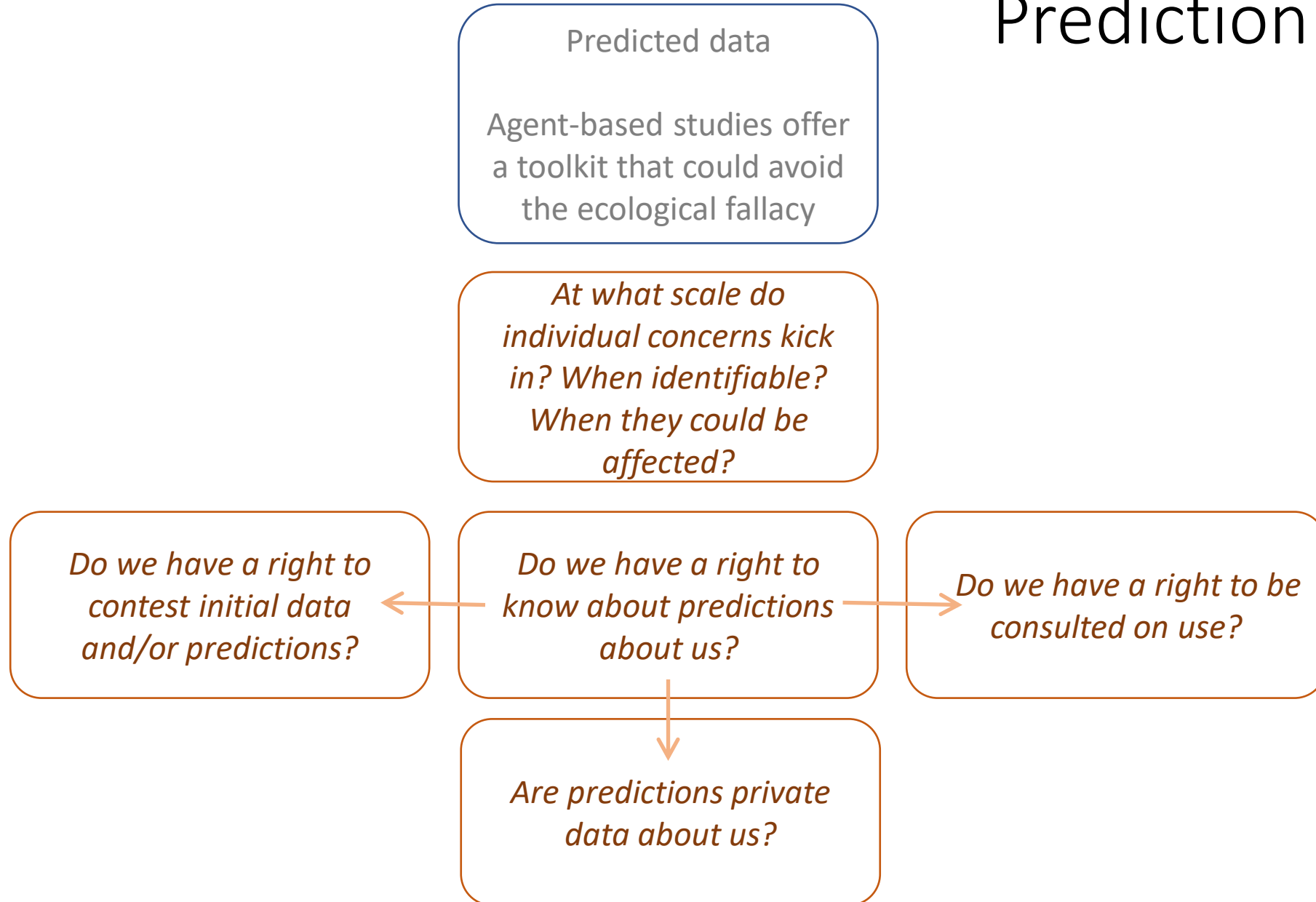
In some cases we'd weigh up by level affected.

However, in some cases there may be inviolable rights.

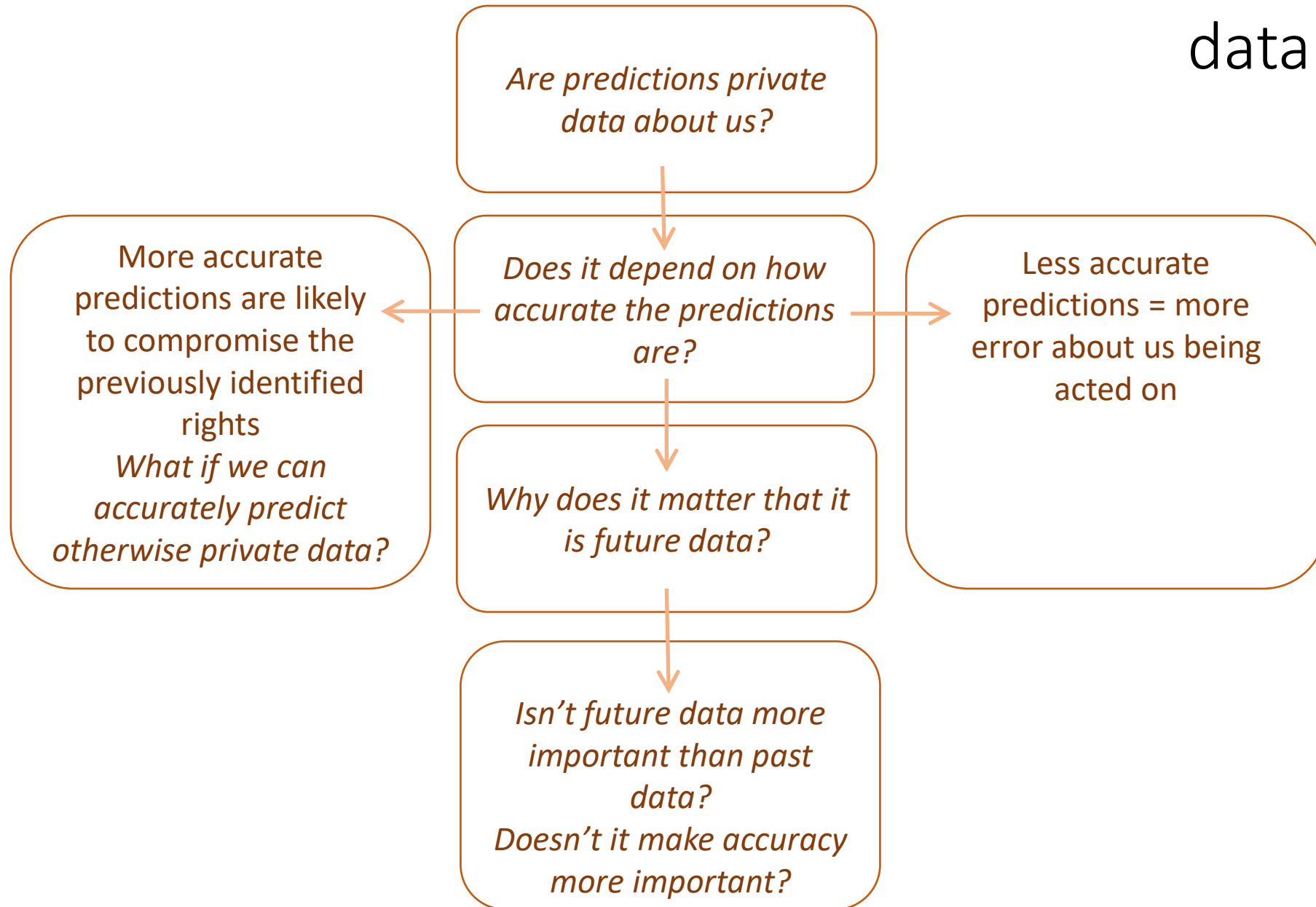
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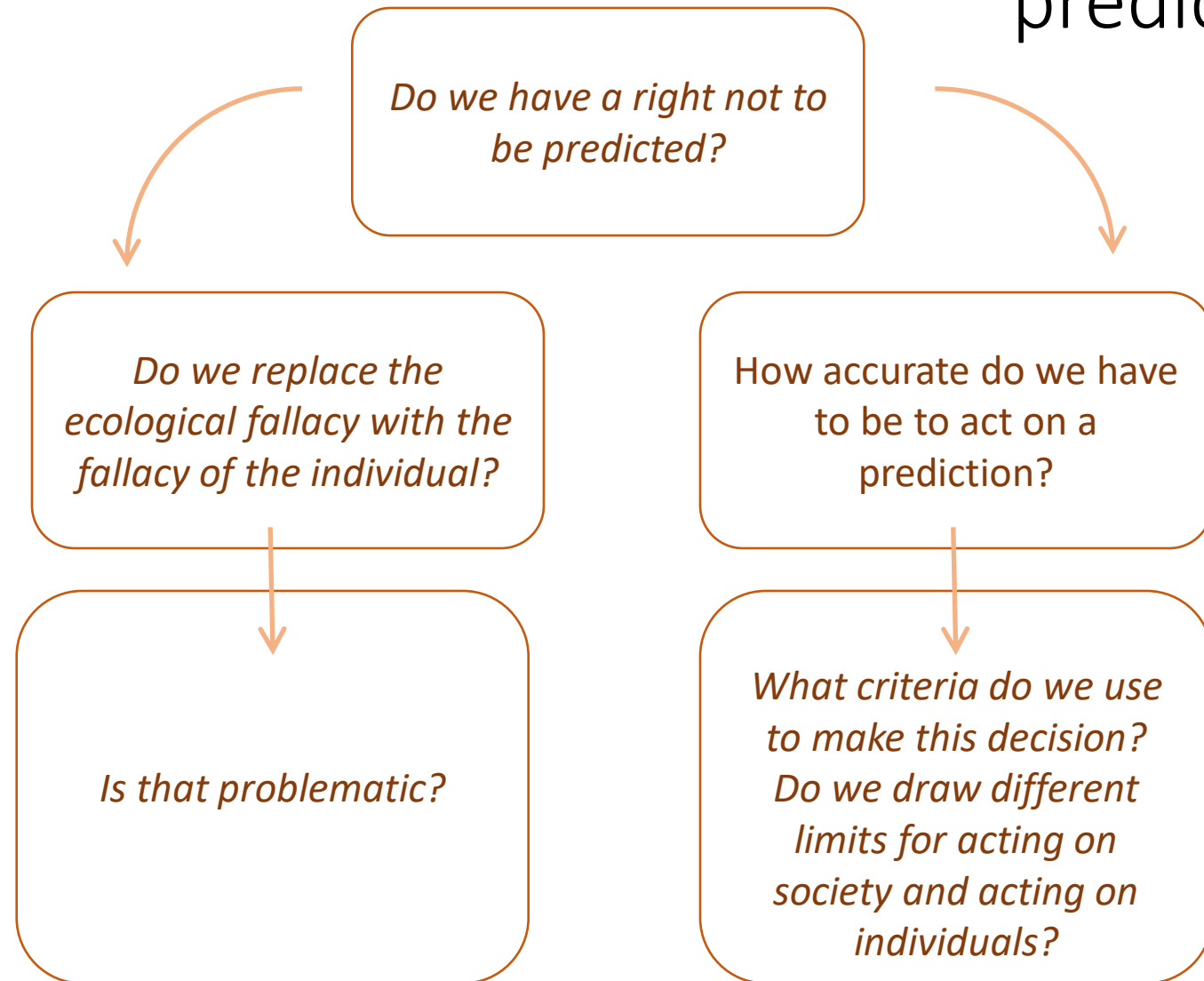
Prediction



Predicted data



Actions on predictions



Issues

Do people have a right to control what their data is used for when non-voluntary?

When/should we model real individuals?

At what scale do we start worrying about individuals?

Are accurate predictions of private data the same as private data generated at a future point in time?