Agent and Multi-Agent Systems: architectures and reasoning

Multi-Agent Based Simulation

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A little warm-up :-)

https://www.wooclap.com/YPMFUO

Table of contents

Simulation

What is a simulation ?

"... The process of designing a model of a real system and conducting experiments with this model for the purpose either of understanding the behaviour of the system or of evaluating various strategies (within the limits imposed by a criterion or a set of criteria) for the operation of the system." [10]

$\rightarrow$ Study a real system through a model in order to understand how does it work and / or to predict its evolution under certain conditions.

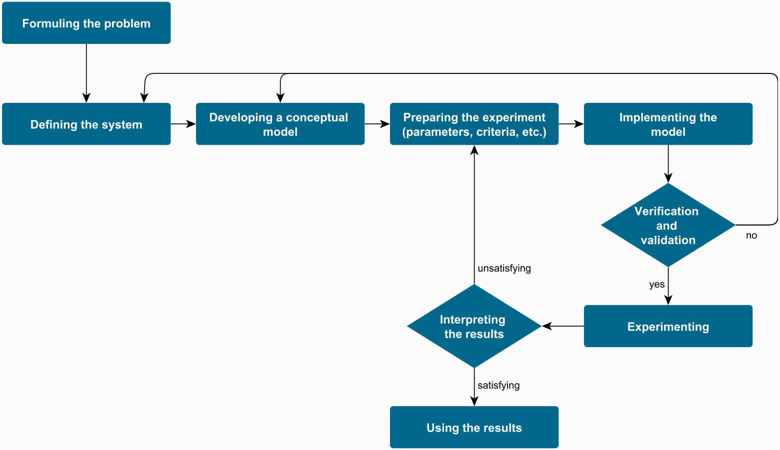
What is a computer simulation ?

> *"Computer simulation is the discipline of designing a model of an actual or theoretical physical system, executing the model on a digital computer, and analyzing the execution output." [3]*

Computer simulation is a **non-linear iterative process** composed of three strongly interdependent fundamental tasks:

1. Developing the model.
2. Executing the model on computer.
3. Analysing the execution of the model and the obtained results.

Computer simulation: An experimental process

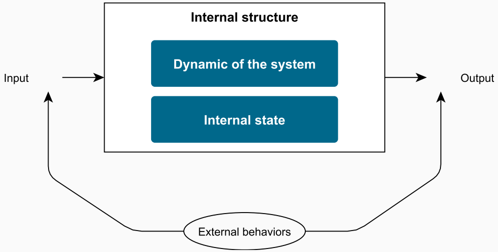


→ Computer simulation is inseparable from the experimental process which is linked to its objective [11].

Introducing dynamic systems

The vast majority of the systems we want to simulate are described as dynamic. Dynamic systems are characterized by:

- The **external behavior** of the system: The observable reactions of the system from the outside.
- The **internal structure** of the system: Its internal state and its dynamics.



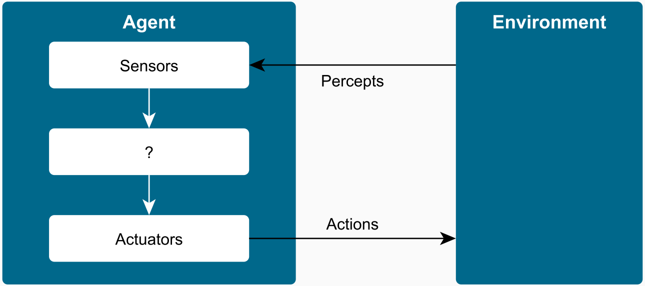
Classic representation of a dynamic system: The black box

Dynamic systems

The internal structure of a dynamic system is defined by three parameters:

- **Internal state**: Define the state of the system (*represented by state variables*).
- **State transition function**: Define how state variables evolve (*from inputs or autonomously*).
- **Production mechanism**: Define how the system produces an output result (*based on its internal state*).

Agent as a dynamic system



Problematic

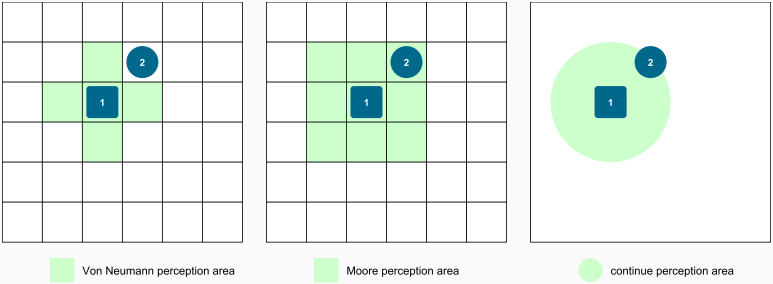
To model and simulate a dynamic system in a computer simulation, one must be able to **specify** it and that these specifications are acceptable.

However:

- The nature of these specifications is not the same according to the knowledge that one has of the system.
- A system can be specified in a lot of ways and with different formalisms.

Problematic

What is perception in the model? How does it work ?



$\rightarrow$ It is important to have a frame, independent from the formalisms used, to model and simulate a system.

Modeling & Simulation theory

M&S theory [13] aims to provide a general methodological basis for the design of a simulation.

M&S theory helps to:

- Identify the different entities that constitute a simulation experiment.
- Study the relations that exist between these different entities.

→ This is to give precise definitions to the different concepts that are manipulated in the field of computer simulation.

Entities in the M&S theory

There are 6 entities clearly defined in the M&S theory:

- The **source system** and its behavioral database.
- The **experimental scope**.
- The **model**.
- The **simulator**.
- The **simulation relationship**.
- The **modeling relationship**.

Entities in the M&S theory

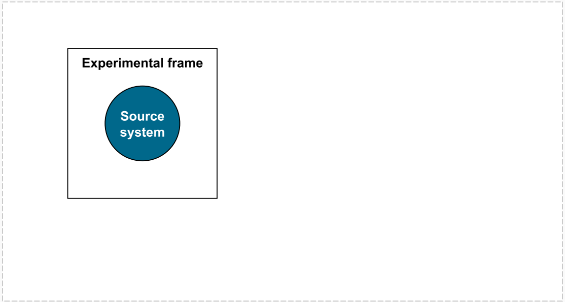
The source system and its behavioral database

The source system corresponds to **the environment to be modeled**. It must be seen as a source of **observable data** that constitutes what is called the behavioral database.

Entities in the M&S theory

The experimental scope

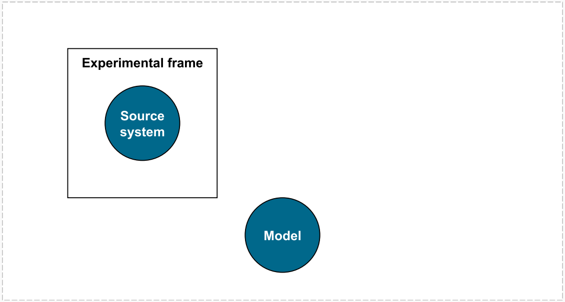
The experimental frame is a specification of (1) the **observing conditions** of the system and of (2) the **objectives of the simulation** project.



Entities in the M&S theory

The model

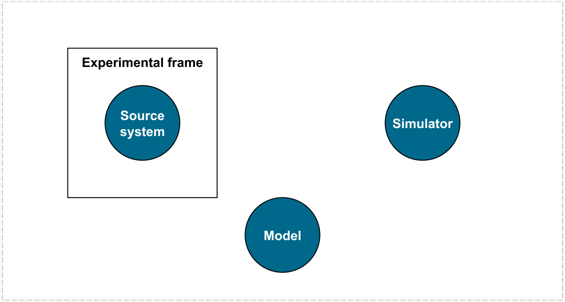
The model refer to the specification of all the instructions used to generate the **behavior of the system**.



Entities in the M&S theory

The simulator

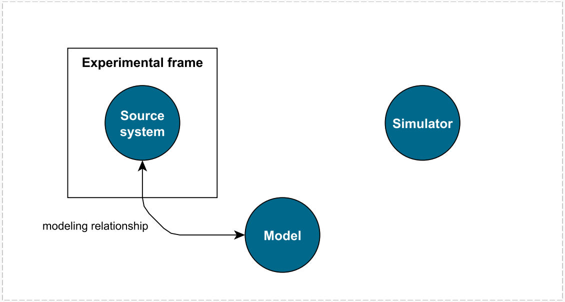
The simulator refer to any **computing system** capable of **executing the model** and generate its behavior. By separating a model from its simulator, a model can be run by different simulators which increases its portability.



Entities in the M&S theory

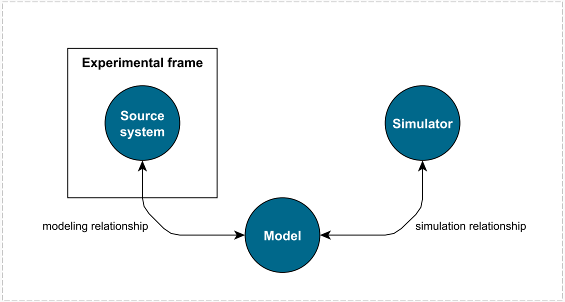
The modeling relationship

The modeling relationship defines the notion of **validity of the model**. *Does the modeling which is made of the system is an acceptable simplification of this one according to the qualitative criteria chosen and the objectives of the experimentation ?*



The simulation relationship

The simulation relationship defines the notion of **validity of the simulator**.
Does the simulator correctly generates the behavior of the model ?
Does the simulator reproduces the mechanisms defined in the model (without introducing errors) ?



Time in Simulation

Time representation in simulation

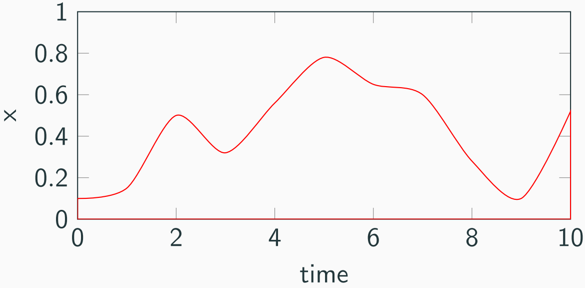
A dynamic system is defined by how it evolves over time. So, one of the most important features of a model which represent a dynamic system is **how time is represented**.

There are three types of time representations:

- **Continuous** time models.
- **Discrete** time models.
- **Discrete event** time models.

Continuous time models

In a finite time interval, the system state variables change in value infinitely often, ie *continuously*.



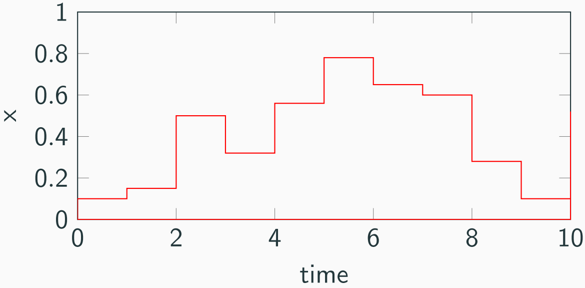
Simulation of continuous time models

The multi-agent approach is far from continuous models because **each change** in the behavior of an agent is always a **punctual event**, and therefore discrete.

$\rightarrow$ The simulation of continuous models raises many problems due to the nature of the computer: It is simply impossible to reproduce the continuity of the dynamics of a system because it evolves infinitely often while the computer simulation needs punctual computations.

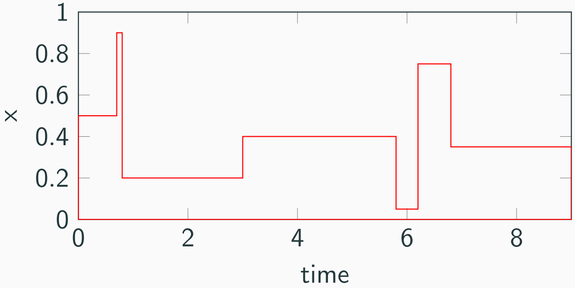
Discrete time models

The time axis is **discretized** according to a constant period of time called time step (dt). The evolution of the system state variables is done in a discrete way, ie *instantaneous*, from t to $t + dt$.



Discrete event time models

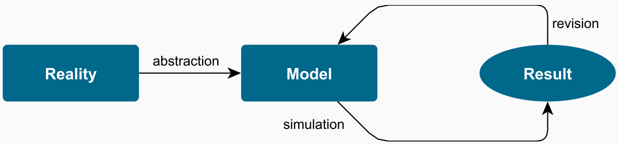
The time axis is generally **continuous**, ie *represented by a real number*. However, unlike continuous models, system state variables change discretely to specific times that are called **events**.



Multi-Agent Based Simulation

Simulation advantages

- Ability to quickly test an hypothesis.
- Highlights the emerging aspects of a phenomenon according to individual choices.
- Highlights the existence of stable situations, resilience capabilities, etc.



Simulation of Equation Based Model (EBM) [7]

- EBM are build on an interrelation of a set of equations that **captures the variability of a system over time**.
- EBM represents **the whole system** and does not support an explicit representation of components (*top-down*).
- EBM is most naturally used to model central systems.

`http://systems-sciences.uni-graz.at/etextbook/sysmod/ebm_vs_abm.html`

Prey - Predator [12]

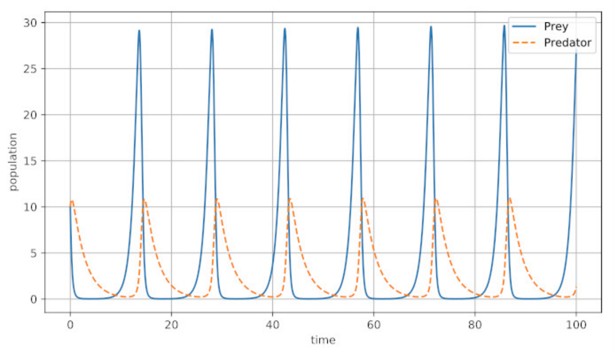
Used to describe the **dynamics of biological systems** in which two species interact, one as a predator and the other as prey.

$$\frac{dx(t)}{dt} = a * x(t) - b * x(t) * y(t)$$

$$\frac{dy(t)}{dt} = c * x(t) * y(t) - d * y(t)$$

$x(t)$	$=$	number of preys over time
$y(t)$	$=$	number of predators over time
a	$=$	preys reproduction rate
b	$=$	preys death rate
c	$=$	predators reproduction rate
d	$=$	predators death rate

Prey - Predator [12]



Source: `https://commons.wikimedia.org/w/index.php?curid=75212926`

$\rightarrow$ Focus on the global variation of the prey and predator populations.

Limits of the EBM simulation

- **Large number of parameters** sometimes hard to understand.
- Difficulty to move from macro to micro level.
- Does not represent behaviors but **behaviors results**.
- Difficulty to represent behaviors.
- Does **not represent interactions and organizations**.

Idea to overcome EBM limits

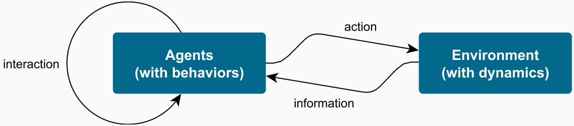
To overcome EBM limitations:

- Use models that **focus on entities and their interactions** (*bottom-up*).
- Consider that **the dynamics** of the system **come from the interactions** between these entities.

$\rightarrow$ Use Multi-Agent Based Simulation (MABS): First works in the early 1990s, has grown since the 2000s.

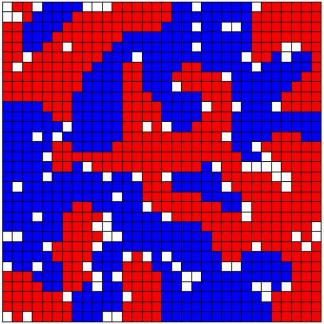
Multi-Agent Based Simulation (MABS)

- Creating an **artificial world** made up of **interacting agents** (*Agent-Based Models*).
- Each agent is described as an **autonomous entity**.
- The behaviour of agents is the consequence of their observations, internal trends, beliefs and interactions with the environment and other agents.
- Agents act and change the state of the environment through their actions.

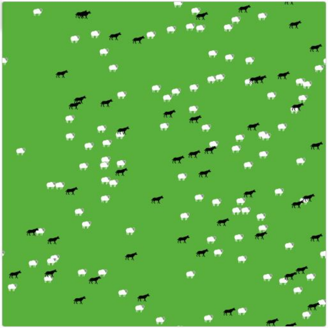


First Multi-Agent Based Simulations

Schelling's Model of Segregation
[9]



Prey Predator
[12]

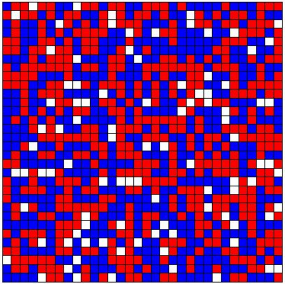


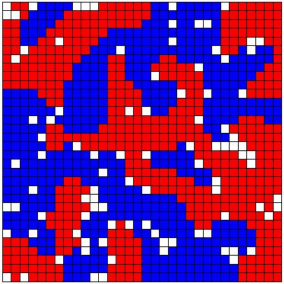
Schelling's Model of Segregation [9]

Study of racial segregation: Shows that segregation comes quickly if individuals want to be with people "like them".

Each entity is represented by an agent and has two behaviors:

- **Stay** (*happy*) if the number of similar neighbors $> x$.
- **Move** (*unhappy*) if the number of similar neighbors $< x$.



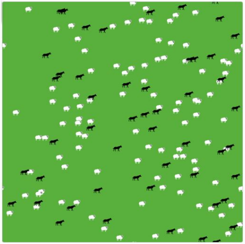


Prey Predator [12]

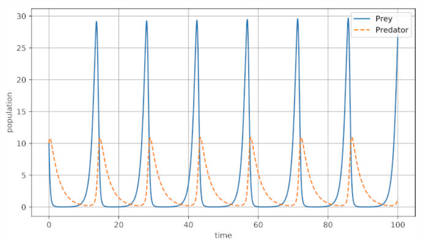
Each entity (prey and predator) is represented by an agent and has behaviors.

- **Prey**: move, eat, reproduce, flee, die.
- **Predator**: move, eat, reproduce, hunt, die.

Each agent activate one of its behavior according to its perception of the environment.



Micro level



Macro level

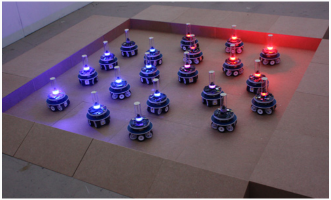
Actual use of MABS

Special effects in movies

Massive software for crowd simulation

Video games

Glassbox engine for SimCity



Collective behaviors for cooperative actions

Collective robotics

Flock of birds simulation

Simulation of complex systems

Actual use of MABS

- Economy
- Crowd movement, emergency and security
- Renewable resource management
- Space Management, development of territory
- Etc.

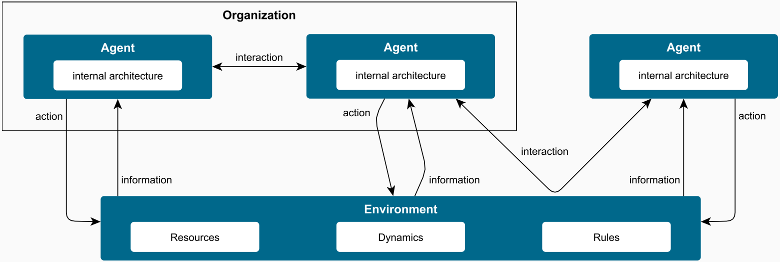
Equation Based Model vs Agent Based Model

Equation Based Model	**Agent Based Model**
Macrospecifications reveal microstructures (*top down*)	Microspecifications generate macrostructures (*bottom up*)
Externally observable phenomenon (*equations*)	Autonomous decision making entities (*agents*)
Simplicity in modeling inputs, state and outputs	Simplicity in modeling rules / behaviors
Internal behavior is unknow	Emerging behaviors
Easy to test	Difficult to validate

Implementing MABS

Development concepts and abstractions

- Define **architecture of autonomous entities** that act in the system (*Agent*)
- Define **interactions** between entities (*Interaction*)
- Define **shared resources** and **processes** between agents (*Environment*)
- Define **coordination** and **cooperation** between agents (*Organization*)



Overview of tools

Specialized tools for Multi-Agent Based Simulation:

- *ATOM, ARCHISIM, MATSim, MITSIMlab*

$\rightsquigarrow$ MATSim: is an open-source framework for implementing large-scale agent-based transport simulations.

Generic tools for Multi-Agent Based Simulation:

- *AnyLogic, GAMA, MASON, SWARM, CORMAS, TurtleKit, Repast, Netlogo, JASMIN*

$\rightsquigarrow$ SWARM is a multi-agent software platform for the simulation of complex adaptive systems. The basic unit of simulation is the "swarm", a collection of agents executing a schedule of actions

Generic tools for multi-agent softwares:

- *Jason, JADE/TAPAS, JADE/PlaSMA, MADKIT*

Implementing Multi-Agent Based Simulation

There are a **significant number of ABM design methodologies and tools** but there is **not yet a standard methodology** that addresses all aspects necessary to define ABM softwares [5].

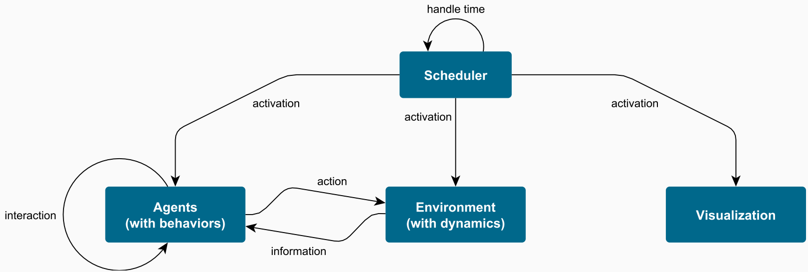
The vast majority of ABM software are built **without the use of reusable agent components and are not generalizable**: Limited adoption outside the academic domain [6].

The **agent paradigm can extend to the object paradigm**. Much of the multi-agent development platforms are based on object-oriented programming [8].

Simulation engine architecture for MABS

The architecture of a multi-agent simulator is strongly influenced by the nature of the source system to be modeled and simulated. Must be taken into account:

- The **nature of the environment** (*continuous/discrete, static/dynamic*).
- The **granularity** of the actions (*fine or coars*).
- The **complexity of agents architecture**.



Implementation of agents and environment issues

The implementation of multi-agent models requires taking into account constraints:

1. **Genericity and modularity** constraint
2. **Locality** constraint
3. **Environmental integrity** constraint

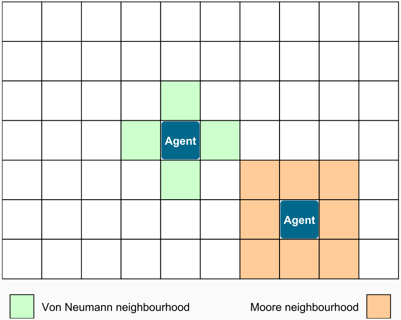
Genericity and modularity constraint:
Individual and autonomous entities are modeled and implemented. We want to be able to vary their implementation without questioning the entire source code.

Implementation of agents and environment issues

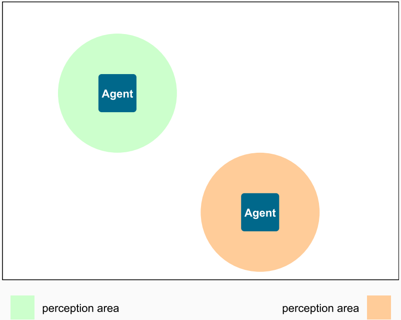
Locality constraint:

The environment is **not fully accessible** to an agent. An agent has only a **local perception of the world** and his actions/perceptions are limited in their scope.

Discrete environment



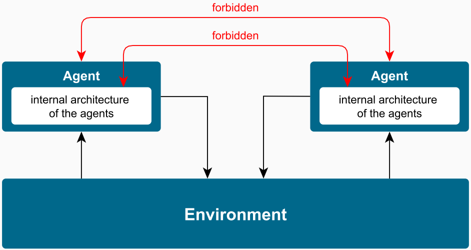
Continuous environment



Implementation of agents and environment issues

Environmental integrity constraint:

- **No direct relationship** between the internal architectures of two autonomous agents
- An agent must **not be able to directly change environment state** variables



Time management in MABS

Need to manage the evolution of time

Multi-Agent Based Simulation is based on the idea that it is **possible to represent a set of autonomous entities operating in a common environment**.

→ All agents must be subject to the same temporal law in order to respect the principle of causality [2].

Agent Behaviour: A Discrete Process

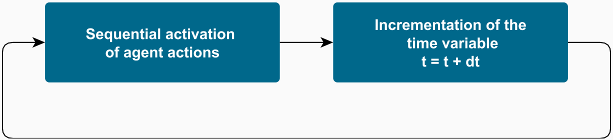
The behaviour of an agent is inherently discrete. The two main implementation principles for handling discrete events:

- **Synchronous approach**: Regular discretization of time.
- **Asynchronous approach**: Event simulation principle.

$\rightarrow$ All parameters that shape an agent's internal architecture and model its behaviour (desires, beliefs, world representation, etc.) change instantaneously.

Synchronous approach

Very simple to use because it only need to program a very **simple function that activates** all the agents behaviors.



Synchronous approach

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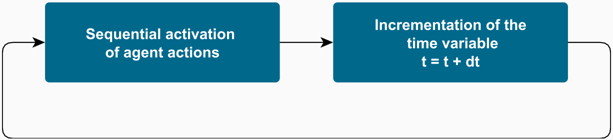
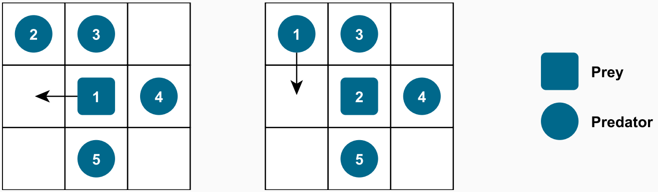


→ The activation order of the agents has a direct impact on the evolution of the world.

Synchronous approach: Order impact

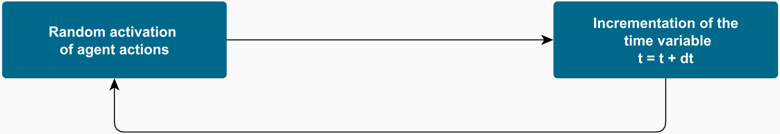


A prey is captured when it is surrounded by four predators following the vicinity of Von Neumann.

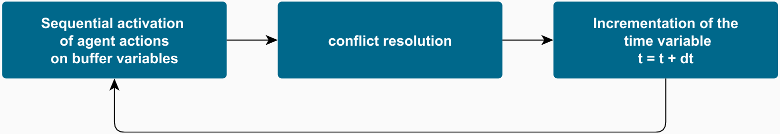
$\rightarrow$ From the same state of the world, the same behaviors can produce different states of the world according to the order of activation of the agents.

Synchronous approach: Random / Buffer memory

Use random activation process [1]



Use buffer variables



Asynchronous approach

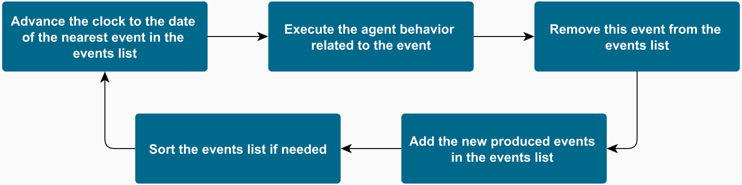
It is hard to picture a reality where a set of entities would be updated simultaneously by a global clock [4].

$\rightarrow$ It is more natural that each autonomous entity evolves at its own pace and generates events whose date of realization is personal to it. The agent activation is asynchronous.

Asynchronous approach

There are two ways to implement asynchronous approach:

- **Events are determined at the beginning** and the simulation consists in executing the list of events
- **Events are determined during the simulation** to take into account the effects of previous events



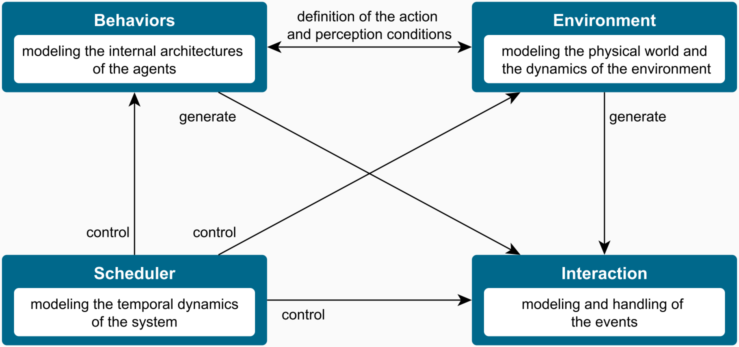
Resume

The four aspects of a multi-agent simulation model

To model and simulate an Agent Based Model, it is necessary to consider four fundamental aspects: Internal agent architecture, environmental model, time management and interaction management.

- **Behavior**: Define the modelling of agents' deliberation processes.
- **Environment**: Define the different physical objects of the world and the dynamics of the environment.
- **Scheduling**: Define how time evolves and the scheduling used.
- **Interaction**: Define the modeling of the result of the actions and the interactions that they produce.

The four aspects of a multi-agent simulation model



Practical Work

Wolf Sheep Predation: a prey predator model to implement

To evaluate the knowledge acquired in this course on Multi-Agent Based Simulations, we suggest you model the *Wolf Sheep Predation* model which is a variation of the prey predator model. The description of the ABM is as follows:

- Wolves and sheep wander randomly around the landscape, while the wolves look for sheep to prey on.
- Each step costs energy. Wolves must eat sheep in order to replenish their energy. Sheep must eat grass in order to maintain their energy. When sheep and wolves run out of energy they die.
- To allow the population to continue, each wolf or sheep has a fixed probability of reproducing at each time step.
- Grass is also explicitly modeled. Once grass is eaten it will only regrow after a fixed amount of time.

Wolf Sheep Predation: it's up to you !

- Implement the described Wolf Sheep Predation ABM.
- Create a visualization interface to setup and run the simulation.
- Write a short description of your implementation choices as well as a description of the behavior of the system and how you find the right parameters so that it is stable.
- Create a zip archive containing the files and upload it on the EDUNAO platform.

Open the document Self-organization of robots in a hostile environment

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