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Artificial Intelligence and Deep Learning

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Forewords / disclaimer

This document is an attempt at synthesizing the Collective and Artificial Intelligence course that I give at the University of Strasbourg and at the Franco-Azerbaijani University. As such, this is still merely a draft, although it contains the essential notions I wish to present during the course. However, it may not be as nicely described as I want: refinement is needed, as well as more proofreading.

The concept of *Complex Systems* is the central concept of this course, even though only the first chapter is dedicated to their introduction. But, as you keep reading, I expect you will be able to understand how all models and notions presented in the course strongly relate to Complex Systems. However, when it comes to artificial intelligence and machine learning, all models relate to complex systems. The objective of this course is to provide an insights about the models that can be used to capture the complexity of real problems, phenomena or situations.

Introduction to Complex Adaptive Systems

Mathematics are not enough to describe the world

Here is a first definition of the notion of "complex system":

> Complex Systems are systems composed of a large number of components and these systems exhibit behaviors that emerge from non-linear (local) interactions between components of the system.

A lot of systems in a lot of different areas can be seen as complex systems (mathematics, economics, physics, sociology, biology, chemistry, ...).

Intuitively, anyone would rely on mathematics to formalize and understand a system or a phenomenon. Mathematics are a set of abstract knowledge that are used for logical reasoning and that can be applied to different objects such as numbers, shapes or structures. For instance, a sphere is an exact mathematical object that is defined, given the sphere is centered at (x_0, y_0, z_0), by:

$(x-x_0)^2-(y-y_0)^2-(z-z_0)^2$

Physics is the science that studies matter, motions and behaviors through space and time. Is there such a thing as an "exact" sphere in physics? What is a "real" sphere if not a mere assembly of interacting atoms? Do this assembly follow the exact definition given above?

Euclide (~4th century BC) demonstrated there is only 5 convex polyhedra and thus, there is no *regular* tiling for a sphere. This can conceptually be illustrated using Fig. 1. The left hand-side of the figure allows us to understand that if a "perfect", exact, sphere were to roll on the curve along trajectory α (in a vacuum), the sphere would go up the hill whereas a "physical" sphere (a non exact sphere, made of arranged atoms) would have to "make at choice" at bifurcation point λ_c and either go along trajectory b_1 or trajectory b_2.

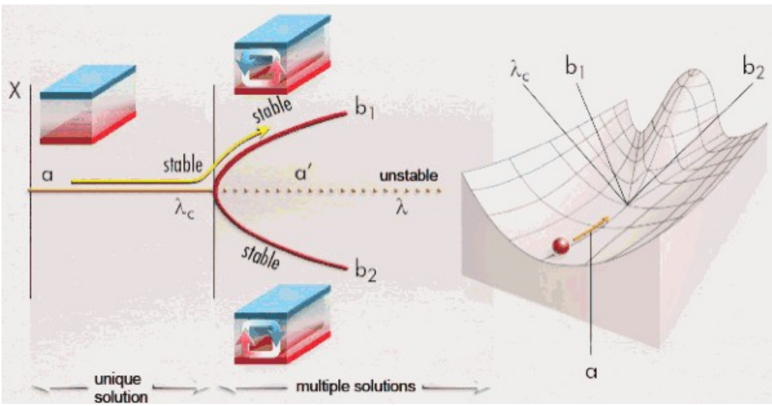


Figure 1: Illustration of a bifurcation, after which the state of a systems radically changes (source : http://www.scholarpedia.org/article/Complex_systems)

A (very) short history of science

It is admitted (and proven) that matter is made of organized and interacting atoms. How old is this concept? Leucippus and his student Democritus, back in the 5th century BC, theorized that the universe is made of two elements: solids and void in which these solids move. Later (380 BC), Aristotle refuted this theory stating that randomly animated particles that would sometime collide and associate, could not constitute matter: according to him, randomness can only produce amorphousness.

Aristotle's ideas prevailed for 2000 years. Scientific revolutions, starting in the 17th century opened the path back to Leucippus and Democritus' view. Around 1600, Copernicus, Brahe, Galilei, Huyghens and Kepler contributed to the geocentric cosmology theory, that matched the observation of the moon rotating around the earth and of planets (and their satellites) rotating around the sun. A few decades later, Newton proposed a model to explain the attraction of 2 objects given their masses and the distance between them. According to this theory, the orbits of these objects should be stable over time. Adding a third objects actually add so much complexity in the system that trajectories can no longer be predicted. It is not because of any randomness, no! The system is perfectly deterministic. However, it is highly sensitive to initial conditions: a slight difference of initial conditions between the actual system and the model, and the trajectory outputted by the model will greatly differ from that of the real system: this is the characteristic of **chaotic systems**. It was Pointcaré, at the end of the 19th century, that highlighted this phenomenon by studying the motion of 3 bodies under Newton's gravitation law. Common examples of chaotic systems include double pendulum[1], Lorenz' attractor[2] or more simply weather forecast[3]. The notion of chaos was very nicely described by Edward Lorenz as

> When the present determines the future, but the approximate present does not approximately determine the future.

Fast forward to the 20th century: René Thom describes the Catastrophe Theory[4], a mathematical branch dedicated to studying **bifurcation theory** in dynamical systems, that is, how slight changes in a system can lead to (unpredictable) sudden and great variations in the system's behavior.

Even if a complex system is deterministic, the core idea of the complex system science is that we cannot predict what will happen but only what *can* happen.

About the notion of emergence

Even though Aristotle's view stalled the comprehension of physics for a long time, he still stated that "the whole is more than the sum of its parts", which is a very accurate definition of the notion of emergence. This holistic approach to understanding system implies that, in order to understand a system, it is not enough to study the properties of its component alone: the system

1 https://www.youtube.com/watch?v=pEjZd-AvPco Accessed Oct. 5, 2020
2 https://www.youtube.com/watch?v=fYdIr6YAp0k Accessed Oct. 5, 2020
3 https://www.youtube.com/watch?v=5qPibjwo21g Accessed Oct. 5, 2020
4 Thom R. (1977) What is Catastrophe Theory about?. In: Haken H. (eds) Synergetics. Springer Series in Synergetics, vol 2. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-66784-8_3

must be studied as a whole in order to capture its emergent behaviors. An artificial neural network is a nice example of this concept: a unit output, on its own, does not have much meaning. However, when (non linearly) combined with other units' output, it's a whole other stories.

Fig. 2 illustrates how combining apparently meaningless components (here, two random images) can produce patterns[5].

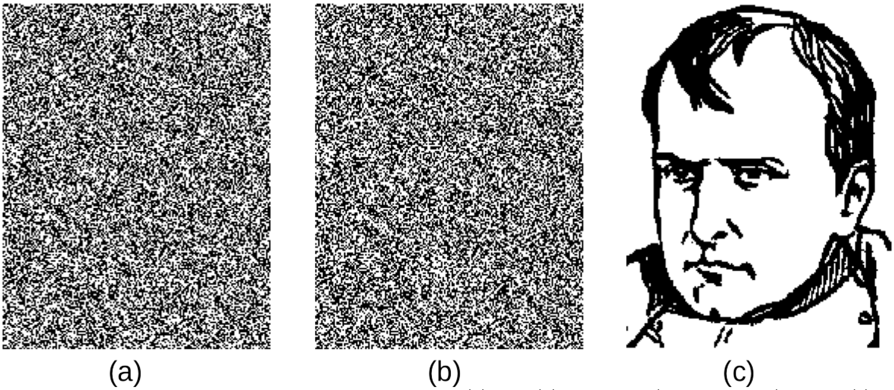


Figure 2: Applying a XOR between random images (a) and (b) produces (non random!) image (c)

What is complexity?

The word "complex" has its roots in latin: *com-* (together) *plectere* (weave). So, a complex system is made of interweaved components. Numerous systems can be described as complex: governments, the human body, organs, ecosystems, etc.

The notion of complexity must not be confused with the notion

5 http://www.scilogs.fr/complexites/le-tout-est-il-plus-que-la-somme-des-parties/ (in french)

of complicated: the traveling salesman problem[6] is complicated (because of its combinatorics) but it is not complex. Complexity relates to things that are difficult to apprehend or difficult to formalize using deterministic logic, such as weather patterns (which are deterministic). Complexity is also related to the idea of chaos and the impossibility to exactly predict the trajectory of a dynamical systems because of its sensitivity to initial conditions.

What is a complex system?

At the lowest level of a complex system, there is a set of individual entities that are indivisible (atomic). These entities are organized and in interaction which influence the system dynamics (behavior). The complexity arises from these nonlinear interactions and, at best, the evolution of the system can only be estimated with probabilities. The behavior of the system cannot be explained or understood at the component level alone!

At the system's behavior level, there is a transition space between order and disorder where the complexity is maximum: this is the **edge of chaos**. Flexible and organized behaviors occurs at the edge of chaos: systems that are too ordered do not exhibit interesting behaviors; this is also the case for systems with no order.

Different metrics can be used to evaluate the complexity of a system. Lyapunov's exponent is one of them. This exponent measure how two initially infinitesimal close trajectories diverge over time:. The left hand expression is the distance between both

6 https://en.wikipedia.org/wiki/Travelling_salesman_problem

trajectories at time t while the right hand expression is the initial separation between both trajectories. When $\lambda < 0$, trajectories converge. In this case, the system exhibits **robustness**: it can go back to the attractor when slightly perturbed. When $\lambda = 0$, the system is in a quasi-periodic state (the edge of chaos). In this situation, slight changes will allow the system to go from a stable periodic state to a chaotic state. When $\lambda > 0$, the system in a chaotic regime: it went in this state following a large perturbation and will "explore" large region of the space phase, possibly finding new attractors that are compatible with the new conditions it is under and then settles at a new, stable, periodic state: the system exhibits **adaptivity**.

Self-organized critical systems[7] refers to systems that are apparently stable, on the edge of chaos, and that can be driven to instability through local perturbation. The sandpile model, depicted on fig. 3, is an example of self-organized critical systems: adding sand grains to a sandpile will gradually increase the slope. At some point, the system will reach a critical state in which, if any more grains were to be added, would cause an avalanche and a slope decrease that would bring the system back into its critical state.

7 Hesse J. and Gross T., Self-organized criticality as a fundamental property of neural systems,Frontiers in Systems Neuroscience (2014)

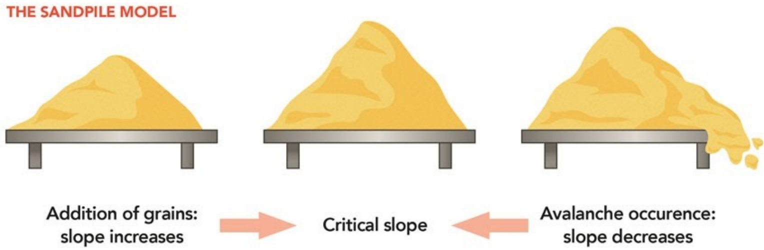


Figure 3: The sandpile model as an example of self-organized critical system (source: https://pubmed.ncbi.nlm.nih.gov/25294989/)

Complex Adaptive Systems

Complex adaptive systems are systems that evolve and adapt when facing perturbations in order to maintain some invariance in its state (allowing the system to survive). It does so by modifying its properties or its environment. The immune system is an example of a complex adaptive system.

The adaptation can be: task based, allowing the completion of an objective; sub-organismic, by maintaining some internal properties (e.g. cell homeostasis); organismic, by maintaining essential properties of the organism and allowing it to preserve its autonomy and its identity (e.g. immune system); ecological, by maintaining patterns of behaviors (e.g. social norms) or evolutionary, that is, at the population level for example by adapting the phenotypic distribution among the population.

More properties complex (adaptive) systems

Complex systems can be further characterized by the following properties:

- Sub-optimality: a CAS does not have to be perfect to thrive in its environment. In other words, being slightly better than its competitor is fine.
- Variety: a CAS with larger variety is stronger because it allows for more “creativity” and new possibilities to evolve in its environment.
- Relationships: the way entities relate to each other is critical for the system’s survival. Those (local) relationships are the source of complexity.
- Simplicity at the component level: the rules governing the behavior of the components are not complex (not even complicated most of the time). Still, the nature of the system (a *complex* system) means that the behavior of the system cannot be derived from those rules.
- Iteration: the evolution of the system is tremendously affected by its initial conditions.
- Self-organization: CAS are decentralized. There is no hierarchy, no leader, no planning. At the system level, all behaviors, patterns, structures emerge from lower level interactions between the components of the system.
- Multi-scale systems: very often, a complex system is made of sub-systems that interact with each others. The human body is a good example of such multi-scale systems: from atoms to molecules and to protein; cells, tissues and organs; to the whole body.

Why study complex systems?

Some phenomena are inherently complex (that is, the system comprises a large number of components which are interacting in a non linear fashion) and may exhibit chaotic behavior. Exacts mathematical models will often fail at providing a solution, an explanation, a description, of such phenomena. Examples of such systems include the study of crowds (best addressed with a multi-agent system), social media or biological systems.

When studying complex adaptive systems, one must keep in mind that these systems are most likely to be multi-scale (space scales, time scale): the complexity is expressed at different levels, and all level of descriptions (from the finest to the largest) must somehow relate. In this case, the tools used to represent the system must scale as well! (using scale laws expressing the functional relationships between quantities, fractals, normalization, ...). It is also necessary to understand that behavior propagates across levels (i.e. compartments are not closed or "airtight" and we may be interested in understanding how this propagation occurs. Basically, fine scales behavior influence large scale behavior (and vice and versa) through nonlinear feedback, dissipation (e.g. Bénard cells), amplification (e.g. butterfly effect, enzymatic activity). At larger scales, we may observe the emergence of patterns (e.g. organ development, residential areas, ...)

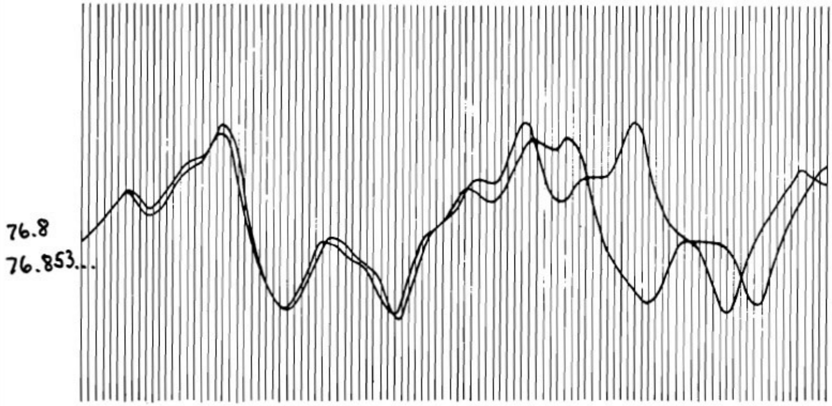
In a complex system, at a quite fine scale, the interactions of the component may seem random but when the system is observed at a macro level, the patterns observed originate from those interactions. Termites mounds are examples of such emergence. The components of the systems, the termites, are, per see, not very complex but thanks to their collaboration and interactions, amazing large structures can be built; structures that have interconnecting passages, caverns and even ventilation tunnels allowing fresh air to circulate in the mound. Similar kind of amazing behavior can be found in ants societies: their nests are oriented, they exhibit foraging behavior, they sometimes enslave other ants from other species, and last but not least, some ant societies can actually farm fungi. Dozens of complex systems example could be cited (to name but a few: the human bodies, human economy, climate and ecosystems, telecommunication networks, ...)

The take home message regarding the notion of **emergence** is the following: complex systems are continuous systems, always "moving forwards", evolving and exhibiting regularities or sudden changes. The structure of CAS is not "hard-coded" (otherwise the macro behavior would not be said to be emergent). Complex systems can be deterministic or non-deterministic (e.g. weather forecast is deterministic). If scientists fail at providing accurate weather prediction, it is because the system is chaotic and a slight error measure at time t will cause a great divergence in the trajectory of the model with regards to the trajectory of the actual system). To wrap up, the notion of emergence refers to a bottom-up process where complex behaviors emerge at multiple scales from the interactions of low-level components.

How can we model complex systems?

First, one must ask themselves a few open questions: what is the question to address: predict a phenomenon or understand how a phenomenon occurs; can the CAS be reduced to a model (i.e. a model will, by definition, loose relevance with regards to the actual system and there is no way to know if emergent behaviors can be reproduce: a component may be missing, a component may not be accurately modeled, or everything that allows behaviors to emerge is present in the model but by "lack of chance" (due to the potential stochastic nature of the system), the simulation of the model does not lead to a particular emergent behavior that the modeler is interested in. Lastly, an important question to address as well is how the model can be validated (and how accurate this validation is).

Models can be **predictive** or **explanatory**. In the first case, the idea is to generate a prediction about the future state of the system (what can happen), preferably before the event occurs (it's too late if a hurricane is predicted right before or at the moment it occurs). In this case, the meaning and significance of variables is not important. It is important in the case of an explanatory model: understanding the role of given variables and how significant they are regarding a given outcome is behind the idea of explanatory modeling.



How two weather patterns diverge. From nearly the same starting point, Edward Lorenz saw his computer weather produce patterns that grew farther and farther apart until all resemblance disappeared. (From Lorenz's 1961 printouts.)

Figure 4: Weather patterns simulation with two slighly different initial condition (source: Lorenz [...]

Weather forecasting is an example of a predicting model. However, the chaotic nature of this system and its sensitivity to initial condition makes it very difficult to obtain a model that allows accurate predictions at more than a few days. Fig. 4 shows how quickly and dramatically trajectories diverge when the initial condition differs very slightly (76.8 v.s. 76.853).

Models are useful to investigate some properties of a system (explanation) or to provide prediction about future states of the systems (prediction) but it is important to keep in mind that a model is (by definition!) and it contains only what the modeler put in it, which means that the model does not necessarily capture all the features of the real system. Modeling intrinsically involves simplification and abstraction: some details must be left out. The modeling process is iterative (fig. 5): from empirical data, a model can be built and run. The model is verified against more data and can be adjusted by modifying its parameters, using new data to refine it, or by extending it.

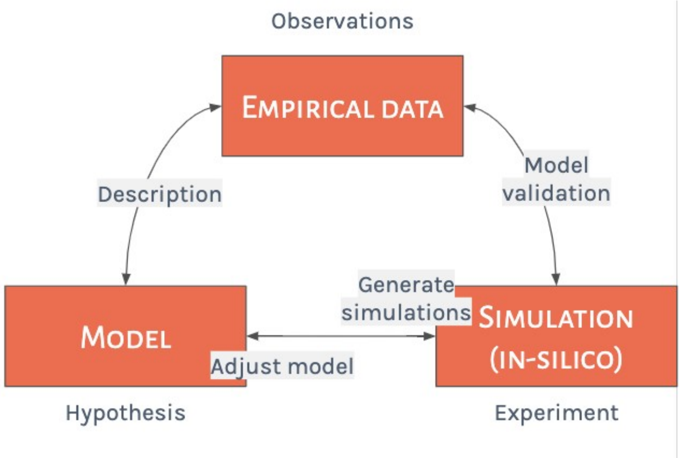


Figure 5: Modeling as an iterative process

Models can be continuous or discrete. In the case of a continuous model, the entities of the model are treated at the population level using differential equations (ODE or PDE). Analytical solutions may be available. If they are not, the model can be numerically integrated. Discrete models involve the modeling of each individual and of the interactions between them. Discrete models include cellular automata or agent based models. In the case of a complex systems, it is of course possible to opt for a hybrid model in order to take multiple scales into account more easily. For instance, a model of cellular tissue could comprise a continuous formalism to model the molecular level and a discrete formalism to model the cellular level. The tissue level need not to be explicit because this is the emergent level of the system.

The **validation** of the model in a given context is an important step of the process: an invalid or irrelevant model is a risk for both the modeler or the user of the model. An example of mishap is the use of the Gaussian Copula model that was partially responsible for the 2008 financial crisis[8]. Dedicated to risk prediction, this model was not intended to be used in the context of stock markets because the correlations between market values are too unstable. Yet, it was widely used and contributed to fueling the crisis.

It is also important to limit risks that are related to the sensitivity of a model/system to initial condition. Different scenario can occur: the precision of the model is limited (76.8 and 7.83 are not the same number!), or stochastic processes can be used in the model. In this cases, maybe that some variables are not required and should be removed from the model (decrease its complexity) and seeds can be set so as to be able to reproduce an experiment. It can also be difficult to estimate how sensitive a model / a system is: a measure of uncertainty can be obtained through multiple simulations of the model in order to evaluate to which extent different simulations diverge given some parameter values (other methods involve using a measure of complexity such as the Lyapunov exponent). In general, to ensure a model behaves well enough, it is important to run a large number of simulation for statistical significance purposes.

Risks are also related to the emerging properties of the system: emergence is, by definition, unpredictable. If an "expected" emerging behavior, observed in the system, does not occur in the simulation of the model, it does not necessarily mean that the

8 https://www.wired.com/2009/02/wp-quant/

model is unable to capture it: running multiple simulation may eventually lead to the observation of an "expected" emerging behavior. Upon observing the invert phenomena, that is, the model exhibits an emerging behavior that was not seen in the real system, increasing the number of observation of the system may lead to the observation of the emerging behavior that the model exhibited.

It can be very hard to identify which components of the systems bring about emergent behavior(s) and the intrinsic abstraction in the model may actually set aside essential components that were not identified as essential: in this case, different models can be used to help identifying the essential components.

Finally, risks are also related to the components themselves: the more components and interactions in the model, the more modeling error there is. Re-using previously validated component can help reducing this risk. It should be noted that only one "faulty" component can impair the ability of the model to fulfill its purpose. Validating the components themselves is not enough: even if their individual behavior seem accurate with regard to the systems, it does not guarantee that, when put together, the model will behave as wanted.

Conclusions

The take home message of this chapter is that pretty much every system can be seen as a complex (adaptive) system. Exact mathematics are not necessarily the adequate tool to represent these systems, and the theory of complex systems provides an interesting ground for such representations. It is however not a trivial process, and, even formally, it is still a work in progress to characterize the notion of emergence. The rest of this course will show mostly examples of complex systems: dynamical systems and multi-agent systems; (deep) neural networks. But now, you know that we will not have much control over them; that their outcomes will be hard to predict and that they are highly sensitive to the initial parameter values we will use.

Application study – population dynamics I

Population dynamics is a field of study in which researcher are interested in understanding how a population evolves over time and how biological or environmental processes influence this evolution (birth rates, death rates, immigration and emigration, among other things). One very simple mathematical model (known as the *logistic map*) for studying population dynamics is the following[9]:

$x_{t+1} = r x_t (1 - x_t)$ Where *x* is the population at any given time *t* and *r* is the growth rate of the population. This equations states that the population at time *t* is a function of the growth rate and the population at time *t*-1. When the growth rate is low, the population dies out and go instinct. When the growth rate is higher, the population might stabilize or fluctuate. For some specific growth rate, the system exhibits c*haotic behavior*.

It means that, for different growth rates values, the evolution of the system will be different. This can be observed on fig. 6. When

9 Visual Analysis of Nonlinear Dynamical Systems: Chaos, Fractals, Self-Similarity and the Limits of Prediction, G. Boeing, Systems 4(4), 37 (2016)

the growth rate is less than 2, the population dies out (fixed point). When r = 0.5, the population is perfectly stable (fixed point). Above two, different dynamics can be observed and, while $r \leq 3.5$, the population converges towards a periodic pattern (limit cycle). What happens when $r > 3.5$?

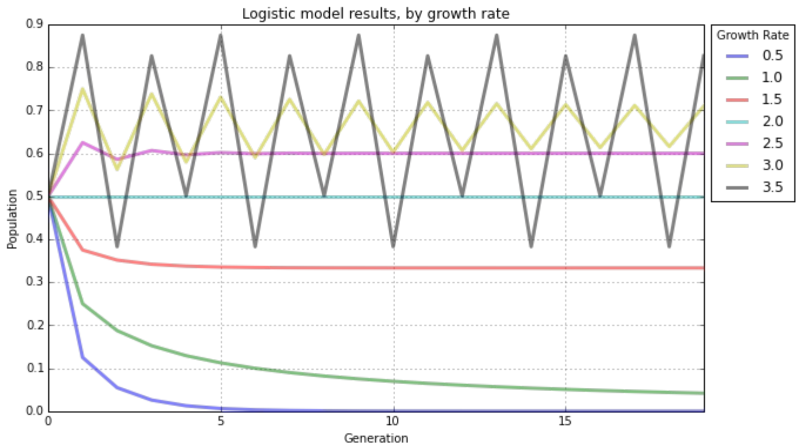


Figure 6: Population dynamics for different growth rates

At the point where r = 3.7, interesting patterns are observable: the population dynamics is no longer stable or periodic: it is chaotic (strange attractor). Fig. 7 below shows the chaotic nature of this model: when the growth rate is slightly changed the population dynamics quickly diverge from each other, although the difference in the growth rate is small.

An attractor of a dynamical system is a value (or several values) towards which the system tends to stabilize over time. There are different types of attractors: fixed points, limit cycles and strange attractors. For instance, the fixed point for r = 0.5 is 0. The fixed point for r = 1 is 0.4. The limit cycle for r = 3.5 comprises 4 values. For r = 3.7, the systems never stabilizes or go back to a value it has already encountered: this is a strange attractor.

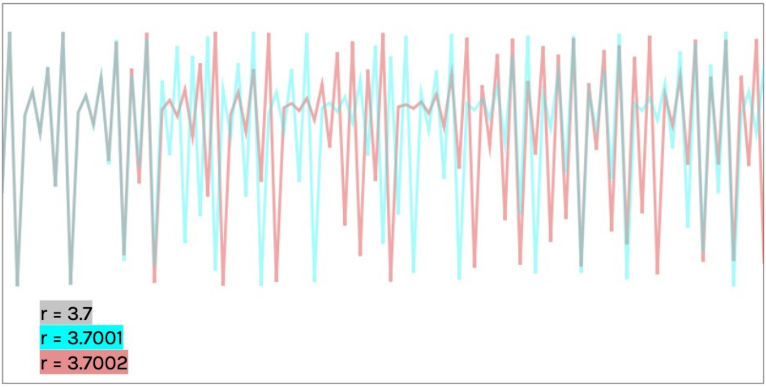


Figure 7: Divergence in the populations dynamics for different values of r

The dynamics of the system can be observed using a *bifurcation diagram*, as depicted in fig. 8.

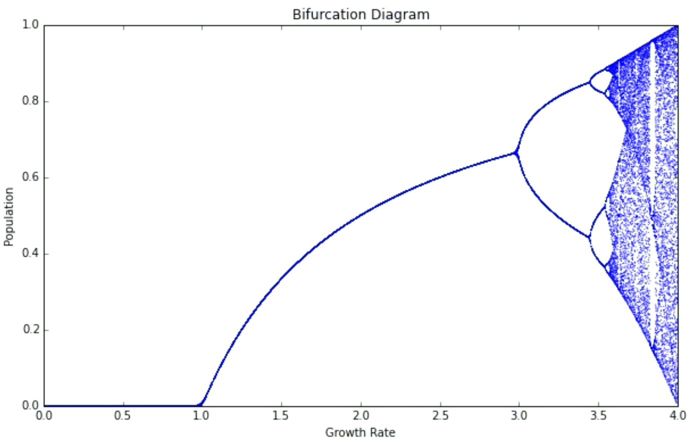


Figure 8: Bifurcation diagram of the logistic map

To plot this diagram, 1000 different growth rates between 0 and 4 were used. This diagram shows 1000 vertical “slices” whose point(s) are the population values that the model stabilized at for a given r (each point of the diagram is the attractor for a given growth rate).

For $r < 1$, the system is never maintained (fixed point = 0). When $1 < r < 3$, the population always stabilizes on one value. For $3.0 < r < 3.5$, the systems oscillates between 2 values. For $r = 3.9$, the population never stabilizes and never reach a same value twice: this is a chaotic regimen.

When r increases, it can be observed that there is a successions of bifurcations between periodic and chaotic behavior. When in a chaotic regiment, the structure of the strange attractor is fractal (i.e. one can zoom infinitely within the diagram and see the very same pattern over an over).

Is chaotic behavior random? Not necessarily! To understand better the chaotic or random nature of a system, it is useful to use a phase diagram, as illustrated in fig. 9: on the left diagram, we see that for every t, the system reach population value 0.65: this is a fixed point. On the right diagram, we see that, between t and t+1, the population oscillates between 4 values: this is a limit cycle.

What does the phase diagram look like when the system is in a chaotic regimen?

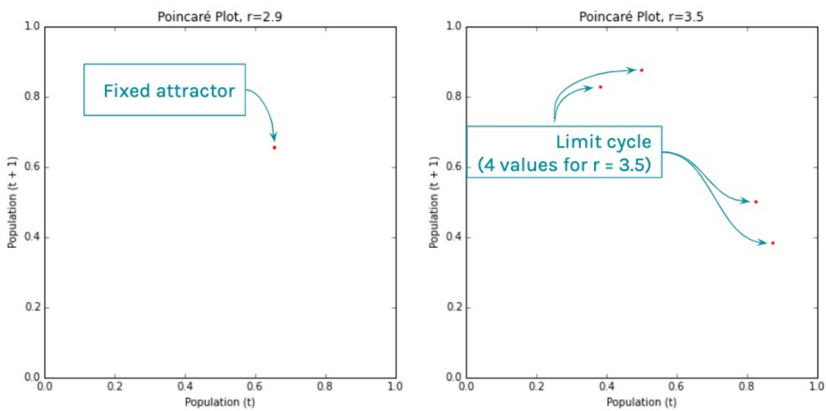


Figure 9: Phase diagrams for r = 2.9 (left) and r = 3.7 (right)

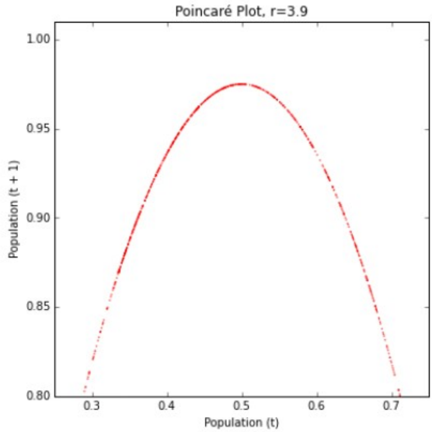


Figure 10: Phase diagram for r = 3.9

Fig. 10 shows the values reached by the population for $r = 3.9$. In this case, the systems reaches different population values, but never the same value twice. This is how chaos and randomness can be distinguished: randomness means that there is a uniform distribution of the values reached by the system. Looking at the phase diagram for $r = 3.9$, it is clear that the distribution is not uniform: in this case, any values can be reached but not randomly (there is a *structure*). This is the reason why a chaotic system can still be a deterministic system! Phenomena simply never repeat.

Fig. 11 shows the evolution of two time series: one is chaotic, the other is purely random. While it is simply not possible to distinguish the two on the left plot, the phase diagram however shows no ambiguity.

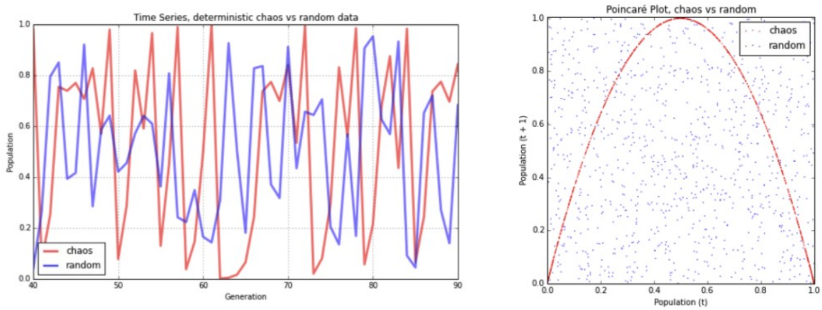


Figure 11: Chaotic and random series

Basically, when dealing with chaotic systems, knowing how sensitive the system is with regard to its initial condition means that accurate predictions would require infinite precision. In the physical world there is no such things as infinite precisions: measure instrument have a limited precision; computers have limited precision. This is why it is so hard to predict the weather.

Multi-agent systems

Agents? Multi-agent systems?

Entity? Individual? Agent? Wikitionary says: From Latin agēns, present active participle of agere (“to drive, lead, conduct, manage, perform, do”) so basically, an agent is someone or something that acts. From a modeling perspective, an agent can be seen as an automated (possibly autonomous) process that can communicate with other agents (in the case of a multi-agent system) to perform a (possibly collective) task.

In the domain of computation, agents are present in numerous domains: connected devices, automation and task delegation, distributed services, ... Agents are often considered as independent (even autonomous), having objectives to achieved (representing the task to solve) and can cooperate or compete with others in order to achieve their objectives.

Multi-agent systems are not just distributed systems: agents have a certain degree of autonomy so synchronization and coordination must occur dynamically at runtime. Agents in a MAS are not necessarily intelligent in the sense that they are not necessarily programmed to learn or understand. A good definition of an a**gent** is given by Woolridge:

> An agent is a computer system that is situated in an environment and that is capable of autonomous action in this environment in order to meet its delegated objectives.

A **multi-agent system** is then an organization of such agents, that can interact with each other in their (shared!) environment. This shared environment is a medium upon which agents can act; it can also be used for interactions if those are indirect (for instance by sending a signal that propagates through the environments, as opposed to agents communicating directly with each other). The organization will mostly be emergent, and is brought about as consequence of the interactions of the agents with other agents as well as with their environment. As a consequence, MAS are more than just a collection of individual agents (recall Aristotle's saying that "the whole is more than the sum of its parts").

In the context of complex (adaptive) systems, the fundamental principles of MAS can be drawn: resources are distributed (available in the environment), the control is decentralized (no grand architect) and the interactions of the agents between themselves and their environments lead to emergent, system level, behaviors.

Although agents and multi-agent systems are related to the Artificial Intelligence domain, an agent is not necessarily intelligent. For example, a thermostat is an agent but is is not intelligent: it merely relies on its **perception** (the temperature, using sensors) to make the decision of performing actions so that the perceived temperature is within a desired point, set by the programmer.

Agents can be **reactive**, that is, they can (to some extent) adapt their behavior in the face of perturbation in their environment (real environments are dynamic: the information perceived by an agent can change, can be incomplete, etc.) in order to carry out their task.

Just like with any kind of models, MAS can be used, for instance, to get a better understanding of a complex phenomenon or be used for problem solving (e.g. using cooperative local solvers).

The basic architecture of an agent is built upon the "perception-decision-action" cycle, as illustrated on fig. 12.

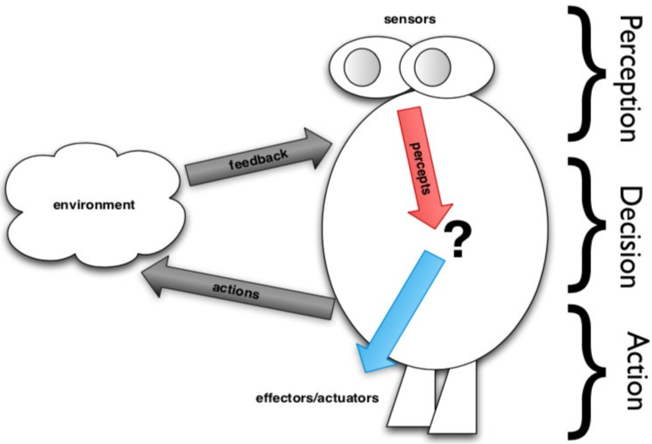


Figure 12: Perception, decision and action cycle (source: T. Payne, univ. Liverpool)

From this point, different classes of agents can be defined. **Purely reactive agents** merely react to instantaneous perception: they have no memory, no reasoning ability whatsoever (e.g.

vacuum bot: if location is dirty then clean). **Reflex agents with state** have an internal state which value depends on the percept history of the agent (e.g. change lane while driving: need to keep track of previously perceived cars). **Goal based agents** have some planning and reasoning capabilities (e.g. the vacuum bot will soon need to recharge its battery: it moves closer to a power outlet while keeping vacuuming along the way). **Utility based agents** are an extension of goal based agent: the difference is that they can weight the "usefulness" of a solution (cheaper, quicker, safer, ...). Finally, **learning agents** are somehow the ultimate goal of agent modeling (and as such, they do not really exist): such agent should be able to evolve in an unknown environment, become more competent and refine their initial knowledge (e.g. the vacuum bot would fine an optimal path to clean in order to maximize the amount of cleaning given its battery life; it would explore the environment to discover the location of power outlets; etc.)

When it comes to defining a Multi-Agent systems, several elements must be examined. The "VOWEL" approach, proposed by Demazeau[10]. {A,E,I,O,[U]} represents the elements that must be defined in order to characterize a MAS:

- A is the set of **Agents**, and the abstractions used in order to define the behavior of these entities
- E is the **Environment**, and the abstractions used to structure the resources shared among the agents
- I are the **Interactions** and how they are defined among the

10 Demazeau, Y. From interactions to collective behaviour in agent-based systems. In Proc. of the 1st European Conf. on Cognitive Science. Saint-Malo, pages 117–132 (1995)

agents

- O is the **Organization**, that is, how agents are structured in the environment
- [optional] U represents the Users

Based on these 4 concepts, the design of MAS can be: Agent oriented, Environment oriented, Interactions oriented or Organization oriented.

In the rest of this document, the notions of “agents”, “organization” and “environment” will be further explored.

Agents

The way agents are built depends on the problem to solve. From this, several agent models can be used (these models can themselves be further classified into the agent classes presented in the introduction). Agents models are defined based on the inputs agents will receive from their environment as well as how these inputs will be coupled to the agents’ actions. There are three main sort of inputs that will influence the model definition: in the **situated agent** model, the agent are mainly focused on the environment; in the **social agent** model, agents also take into account the interactions they have with others (request –may modify an agent’s behavior, inform –may change an agent’s belief; either privately –to a single agent—or globally –broadcast); in the **organized agent** model, agents also take into account how the organization, the social structure, of the system influence these interactions (e.g. penalize/reward interactions given its outcome for the society; respect rules). The two main ways of coupling the agent's inputs with their actions are through **reflex agents** and **deliberative agents** (includes *goal based agents*, *utility based agents* and *learning agents*). It is also possible to define a hybrid agent, that will, given the circumstances, be able to be purely reactive or to deliberate about its actions given its percepts.

A (purely) reactive agent (fig. 13) acts merely in a stimulus/response manner. It has no explicit representation of its environment, of its capabilities (otherwise it would be able to reason or deliberate) or of the other agents. As previously stated, such agents do not have any memory of past actions or percepts and they have no planning abilities.

On the other hand, **deliberative agents** (fig. 14) have an explicit representation of their environment (including of the other agents) and of their abilities. They can reason and plan based on their internal state before undertaking any actions.

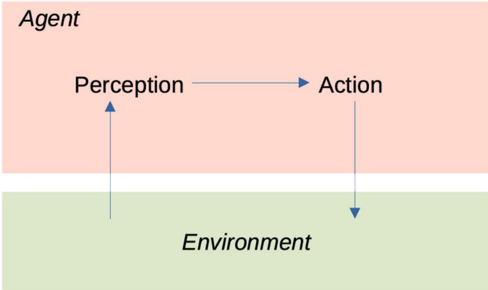


Figure 13: Cycle of a reactive agent

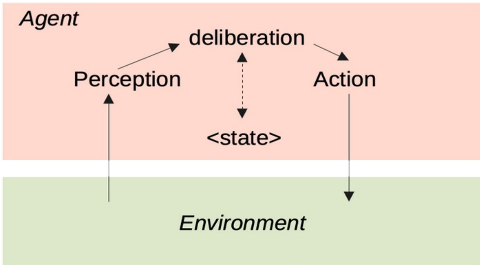


Figure 14: Cycle of a deliberative agent

Environment

The environment in which agents / MAS evolve is characterized by the following properties:

- Observability. Is the environment fully or partially observable? Can agents access complete and accurate states of the environment at all time? Even if, in a virtual environment, agents can be programmed so that they can fully observe (perceive) their environment, this is highly unrealistic. Agents will most likely be able to perceive a local patch of their environment.

- Agentivity. How does a given agent consider other entities in the environment? (e.g. in the case of a driving agents, are the others cars agents or mere physical objects that happens to be there?)
- Stochasticity / determinism. Is the next state of the environment entirely defined by the current state and the agent's actions? If the environment is partially observable, should the environment be regarded as stochastic? (e.g. a driving agent cannot predict/anticipate all possible behavior of the other cars)
- Episodicity / sequentiality. Do current decisions affect future decisions?
- Static / dynamical. Can the environment change while an agent is deliberating about an action? What about synchronicity?
- Discrete / continuous. Is space continuous or discrete (with what topology?)? How is the time handled? (e.g. agents playing chess v.s. agents driving cars)
- Structure. Do environment know about the laws of the environment? (e.g. physics)

More generally, it is also important to think about the following (non exhaustive) questions when designing the environment of a MAS: does the environment keep track of the agents? Are interactions local? Is there a shared message board for agents to use for global signaling? How are resources managed (e.g. mutex)? How is time handled? How are the agents scheduled? What about multi-scale phenomena?

Organization

The organization is something that occurs at the system level. In the case of a complex system, this organization is emergent and implicitly implemented in the interactions between the agents and between the agents and their environment. It is also possible to pre-define (parts of) the organization, for example by assigning tasks to agents or by defining norms (such as behavioral or social norms). In this case, the pre-defined (parts of the) organization can be considered as a help provided to the agents. It does not mean that not emerging structure will emerge, so the systems may still be a complex system.

Multi-agent approach for modeling

Just like most entities composing “real life” complex systems, agents in MAS are heterogeneous and so are their interaction: this can be very difficult to capture using a modeling formalism such as differential equations (DE), because they focus on the populations rather than on the individual.

The modeling approach with a MAS is constructive (from the bottom up) where elementary local operations are modeled rather than relying on a global “black box”. But a MAS is a complex system itself, in particular it has a lot of components (agents) and parameters that can be very difficult to adjust. Unlike some DE models, no analytical analysis of a MAS is possible: it means that simulations of the systems must be systematic to be able to observe the behavior of the model.

Using MAS as a formalism for modeling, it can then be quite tedious to explain emergent results / system behavior as well as to compare the model to the real system. It does not mean that MAS are not useful. They are used in numerous application domains: to study the real world (biology, population dynamics, epidemics dynamics, ...; urbanism; economy; social science); to study crisis response, for example by studying evacuation scenario in buildings and, of course, they are used in entertainment (movies[11], video games[12], ...)

Finally, regardless of the type of model one wants to use, one crucial step in modeling is **the question one wants to address with their model**.

Conclusions

The world of MAS modeling is far bigger than what was presented in this chapter. However, this introduction allowed us to better frame the notions of agents and multi-agent systems. The VOWEL approach proposed by Demazeau is a very convenient method to design MAS even though some aspects of MAS design are hard to apprehend (parameters, granularity, simplifications, ...). A lot of MAS are complex systems and as such, it is expected that they are not always easy to manipulate.

11 https://en.wikipedia.org/wiki/MASSIVE_(software)
12 https://arxiv.org/abs/1902.04043

Exercise

Read the following article and explain how a seemingly simple event led to an amazing emergence https://phys.org/news/2018-11-yellowstone-streams-recovering-wolf-reintroduction.html

Application study — modeling population dynamics with ODE

A farmer wants to control the aphid population in their fields by introducing a predator: ladybugs. Let P be the number of aphids in a field at time t; b is the birth rate of aphids and m is the mortality rate of aphids.

Population dynamics of aphids without a predator

Using both birth and mortality rates, the variation dA in the aphid population can be expressed as a function of time:

$\frac{dA}{dt}=bA-mA$: at each time t, the total number of aphids is increased by the number of new born aphids and decreased by the number of aphids that "naturally" died. This can also be expressed as $dA/dt=rA$ where r is a growth rate (r = 0 means the population is stable; r < 0 means the population decreases; r > 0 means the population increases). This term does not *explicitly* model the resources available in the environment (*i.e.* we could add an equation to depict the amount of produce consumed by the aphids).

To study the evolution of A, we must find a solution to $A(t)$ such that its derivative is $rA(t)$. Some systems do not have analytical solutions. In this case, we still can numerically integrate the system (provided an initial value for $A(0)$).

Note that in general, populations do not follow an exponential growth but rather a logistic evolution that depicts the maximal "load" that an environment can sustain.

Introducing a predator into the model

Let L denote the population of ladybugs and k be the predation rate. The proportion of preys killed is proportional to the number of ladybugs L and the dynamics of the population of aphids can now be expressed as $\frac{dA}{dt} = rA - kAL$.

Population dynamics of ladybugs

Just like aphids, ladybugs reproduce and die. First, let m_2 be the mortality rate of ladybugs in case of famine (no prey):. The population L increases if sufficient resources are provided and the growth rate of L depends on the population of aphids A. Let e be the rate at which aphids are eaten by ladybugs: $\frac{dL}{dt} = -m_2 L + eLA$.

The complete model for the Aphid/Ladybug population dynamics study is then:

$$\frac{dA}{dt} = rA - kAL$$
$$\frac{dL}{dt} = -m_2 L + eLA$$

It is the Lotka-Volterra system[13]!

13 https://en.wikipedia.org/wiki/Lotka%E2%80%93Volterra_equations

Application study – modeling population dynamics with a multi-agent systems

Two species share a habitat. One species preys on the other. Before we diving into the modeling process, there was probably a question that led someone to want to build a model. Such a question could be *"how do the population levels of two species change over time when they coexist in a shared habitat?"*.

A more precise question is: *"Can we find model parameters for two species that will sustain positive population levels in a limited geographic area when one species is a predator of the other and the second species consumes resources from the environment?"*[14].

What are the agents (and what is their granularity, i.e. atoms? Cells? Individuals?)? What are their behaviors? How about the environment (is it continuous? Discrete? Is it a tore?)? What about the time? (e.g. herbs grows quite slowly compared to the time needed for a predator to chase a prey)

Why is MAS a good model candidate for this system? We have

14 From Introduction to Agent Based Modeling, Wilensky & Rand

already studied a model for population dynamics (the logistic map), so why this change of paradigm? MAS is a good choice because it permits to tackle the **"nano-sheep" problem**: if we use a continuous model such as the logistic map, the populations are expressed as a continuous quantities. At some point, we may find a millionth of a prey in our system. The individual-based paradigm offered by MAS is an easy way to get rid of nano-sheeps. Moreover, the flexibility of MAS allows the modeling of **heterogeneous agents** (what if a single sheep in the herd actually defends itself?). Also, MAS is great for taking into account **spatial locations**: a predator cannot eat a sheep if it located far far away.

The agents and their behaviors

Let us define 2 main agents types in the model: wolves and sheep. Both species can (1) turn randomly (i.e. change direction randomly), (2) move forward, (3) reproduce and (4) die ("old age", energy deprivation, being killed by a predator).

Wolves consume sheep (remember to take spacial interactions into account), sheep consume grass and grass can regrow (grass was not registered as an agent since it does not have "acting" behavior –in particular, it doesn't move— but this is nothing more than a modeling *choice* –it doesn't mean it's right or wrong).

Resource consumption allow agents to keep energy level high enough to live (just like us).

Other modeling questions arise: is the reproduction of species asexual? How about moving in packs? Can predator track a prey? Can prey defend themselves? Do agents sleep? How do they process food? At what rate do species consume resources? Etc.

Al lot of questions can be asked. All questions do not have to be explicitly treated, but each time a choice is made (even if the choice is, for example, to leave out one particular point), it must be clearly stated so the model is as transparent as possible).

The environment

The base environment is simply a field of grass (that can be consumed by sheep). But here again, different modeling choices can be made: how about the terrain elevation? Water? Woodland?

Is the environment bounded? Infinite? Is it a torus?

Setting up the model

Now, a simulation step must be defined (i.e. what happens during a “slice” of time?): agent’s behaviors must be scheduled (which behavior occurs first, which agents program is executed first).

The parameters of the model must also be set. Most of the time, this is an iterative and empirical process (this is actually one of the things that’s very hard when using the MAS paradigm to model a system).

What is the initial number of sheep? Wolves? Grass? What does an action cost in terms of energy (movement, reproduction, ...)? At what rate does the grass regrow? What is the reproduction rate of agents?

Then, a measure allowing answering the questions we want to address with the model must be picked, e.g. keep track of populations counts over time.

A framework for MAS simulation: NetLogo

A lot of modeling platforms and frameworks are available for MAS simulations[15]. NetLogo[16] is one of them. It is very easy to get started with MAS modeling (especially since it contains a lot of predefined systems that can simply be ran in the software) and it is thoroughly documented[17].

15 https://en.wikipedia.org/wiki/Comparison_of_agent-based_modeling_software
16 https://ccl.northwestern.edu/netlogo/
17 https://ccl.northwestern.edu/netlogo/docs/