Coevolutionary strategies in MultiAgent systems. An approach using socionatural realistic environments.

Master Thesis

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Abstract

The aim of this master thesis is the development of a multiagent model for a simulation of two populations whose interactions are strongly influenced by a realistic landscape. This research will be in line with Consolider-Simulpast (www.simulpast.es), an interdisciplinary project aimed to create simulations designed to be used in archaeological studies of human-environment interaction, decision-making processes and coevolutionary/competition behaviours of past societies. The work plan will be focused on the development of first-stage models for two societies in the age of agriculture spreading surpasing the hunting and foraging way of living. The simulation will involve a climate engine for seasonality depending primarily on variable rainfall rate. Landscape information will be created from satellite image rasters. Constants, and variable relationship shall be modelled from measures and interviews with the experts. Data analysis tasks will be undertaken to validate the models and detect patterns in the archaeological record. Furthermore a comparison will be stablished between the classical simple models used in social simulation[1][2][8] and more advanced approaches.

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Chapter 1

Introduction

1.1 Description

1.2 Motivation

Simulation has been following an evolution in the models and paradigms applied to represent its target systems. Dynamical systems, differential equations have been used and an overall simplification of the parts of the systems in the history of simulation to operate with the abstraction and simplification of the problems. Mainly, reusing ideas from physical simulations, social sciences has modelled complex systems with dynamical atomic entities that apply a simple set of centralized rules to move around the environment modelled. It was seen that due to the deeper details in human behaviour the question that could be solved and asked to that kind of models could not go very further as expected.

To solve non-linearity phenomena, heterogeneity, hysteresis[46, p.571–597] and other issues typical of complex systems, Agent Based Models(ABMs) where introduced to gain more insight of the modelled systems achieving good results. But under some conditions of very complex relationships between agents, highly specialized decission taking procedures and issues in the environment led agents to need a sophysticated reasoning and problem solving capabilities that are not specified and not yet introduced in ABMs coming from Social Sciences.

We have found an example of that situation in our case study located in Gujarat from Simulpast project. Our agents must interact with a regular but changing environment to get resources, plan its actions, coordinate with its group and compete with other groups in a **co-evolution** dynamic. Because we want to find out why the Gujarat HunterGatherer(HG) way of life lasted more than in other place of Earth in its competition against AgroPastoralist(AP), we need to embed the behaviours of the survival strategies used by these groups. A simply reactive agent cannot cope with short term plus long term decissions in that competitive environment. So the question stated as topic for this Master Thesis project is **“do we get better results in social sciences simulations adding deeper AI techniques to make richer the behaviour or decission making engines of the entities in the system?”**. As we understand “better results“, the outcome from the use of AI should be a more sound validation of the model, a nearier match of modelled behaviours with the real ones, and clearer, richer and robust scientific conclusions.

In order to study such posibilities Sugarscape is a good framework to extend. Sugarscape is an artificial society developed by Joshua Epstein et al [2]. where a number of inhabitants move to collect resources they need to live. Sugarscape models perception, lattice scanning in search of resources, sexual reproduction of the agents in the simulation, market relationships, immunology and spreading of diseases, and feature evolution. Epstein analises different experiments executed in the Sugarscape offering his conclusions and the dynamics emerging from the simulations. The results and conclusions will feed our AI experiments in order to make the comparisons of classical SugarScape agents vs AI agents, therefore, giving an answer to the topic of the Master Project.

1.3 Simulation

Simulation is a discipline for performing virtual experiments in a computer. Computational techniques are used to build a model that represents your system. The dynamics of that system is codified in an algorithm that computes a calculus imitating the changes of state in the model, hence having a representation of that change along the time of the system modelled. Simulate is to play to ”what happens if...?”, and it is aimed to discover and explain the dynamics of a system to enhace or guide strategy development, decission taking, management, solving problems without analytical solutions or knowledge discovering and research. Although, we could get other positive benefits from it like theory checking or training through the inmersion in virtual worlds responding to our input.
A simulation obeys some direction of experimentation, so a question must be set to drive the selection of features to model from the real system and give a direction to the modelling and the experiments design.These assumptions choice will prune the details not related to the questions to solve. It is not just for the sake of simplicity but for the practical reason that a model too near of the real system will be as hard as the original system to analyse.
Simulation, like deduction, starts with a set of those explicit assumptions. But unlike deduction, it does not prove theorems. Instead, a simulation generates data that can be analysed inductively. Unlike typical induction, however, the simulated data comes from a rigorously specified artificial experiment rather than direct measurement of the real world. While induction can be used to find patterns in data, and deduction can be used to find consequences of assumptions, simulation modelling

can be used as an aid intuition and hypothesis validation tool. Also as space search mechanism for parameter tunning or optimization. This links with abductive processes.
Just like in a tipical Sherlock Holmes case you pick the evidences, scenario for the experiment, and the common knowledge (the initial expert assumptions about the model). You enter in a refinement cycle where you test hypothesis and readjust them to discover the theory, the "plot", the explanation of what is happening. Following the abductive reasoning schema one looks for the hypothesis that would best explain the relevant evidence [4].

Social simulation is a research field that applies computational methods to study issues in the social sciences. The issues explored include problems in psychology, sociology, political science, economics, anthropology, geography, archaeology and linguistics [43].
Social simulation aims to cross the gap between the descriptive approach used in the social sciences and the formal approach used in the hard sciences, by moving the focus on the processes/mechanisms/behaviors that build the social reality.
In social simulation, computers supports human reasoning activities by executing these mechanisms. This field explores the simulation of societies as complex non-linear systems, which are difficult to study with classical mathematical equation-based models. Most of the times, studying complex systems implies to cope with non reducibility. One of the examples is Gravitational Dynamics. If our assumption is the use of Newton's mechanics, we can predict the state at any time or not, depending on the scenario. For a one dimension world you can predict the state at time t_n from the initial state t_0 without computing all the preceding ones. For two and more dimensions you can only compute directly state t_n if less the three bodies are implied. So in a real environment of many bodies in a 3D world you need to compute all the states from the initial to the one you consider as the last one. The system is non analytically reducible and you are forced to apply simulation to visit all the states and develop the behaviour of the model. It happens in most of the complex systems models, they have a nonlinear specification. Nonlinear models do not have a simple or computational reasonable analytical solution.

Other of the main issues in complex systems simulation is emergence. While the initial assumptions may be simple, the consequences may not be at all obvious. The large-scale effects of locally interacting entities are called "emergent properties" of the system. Emergent properties are often surprising because it can be hard to anticipate the full consequences of even simple forms of interaction.

There are some models, however, in which emergent properties can be formally deduced. Good examples include the neo-classical economic models in which rational agents operating under powerful assumptions about the availability of information and the capability to optimize can achieve an efficient reallocation of resources among themselves through costless trading. But when the agents use **adaptive** rather than optimizing strategies, deducing the consequences is often impossible; simulation becomes necessary.

1.4 Question

In classical simulation approaches, specifically in the branch of Social Simulation, active entities which model human actors are designed with very simple behaviour engines. The classical hypothesis is that a complex mind for entities in the simulation are not that needed and maybe even could lead to difficult analysis of final results of the simulations (too daring statement?).

Our statement is that, on the contrary, the mind engine of a simulation entity should not be bounded to that limit but special attention must be paid to give any necessary sofistication to give the entity a correct behaviour, real enough, sensible to the changes in the environment and competent to solve the issues that will have to solve along its lifetime in the system. Even more, we think that this entities' capability to respond with complex behaviours is the core that roots the modelling granularity needed to catch the essential of the social systems that we want to model. Applying such premises we will explore the possibility to give or enhance decission making, problem solving capabilities to the entities with the aim to get more accurate simulations and realistic models with higher matching against our job hypothesis and premises. We will take the framework of ABMs to integrate the AI techniques in a decission making schema of action-response dynamics sensible to a modelled world.

Do AI techniques contribute to better simulation results?
Classic Simple Agent approach vs Rich Agents
Did Gujarat extreme enviromental conditions delayed the HG disappearence?

Chapter 2

Methodology

2.1 Intro

Modelling is a widely extended methodology to answer the kind of questions we set out. It comes from the natural observation of the world and the curiosity or need to reproduce it.
The modelling activity determines aspects of the world to include or exclude from the details that will conform an abstraction of the world that will allow work the answers [21].

Modelling will be our framework for communication between archeologists' and sociologists' knowledge and their conceptualizations with our formal representations from computer science practices(simulation, algorithms, AI). The reason is that it is a procedure that will help to communicate the **discursive** nature of Social Sciences with the formal structures from Computer Science. The engi-nering of model development will allow us to reach a connection from experts' knowledge to a model that comprises the set of detail clearing out the ambiguity that language could filtrate. Also, modelling will help set a picture of the system without inconsistencies, with each fact sound, coherent and consistent from the logical point of view with the whole.

2.2 Why model

The modelling process consists in identifying separable entities, processes, relationships and any rellevant information related to the question to solve and the domain of study. This abstraction exercise yields an external and explicit representation of part of reality as seen by the people who wish to understand, to change, to manage or to control that part of reality [20].
Indeed just thinking about something implies an unconscious projection of our mental frame hence producing a set of concepts and relationships that give birth to a model. The missed step is that it was not made explicit through some formal

representation. A model is a logical and conceptual prototipe.
As Epstein [3, p.1] says *"Anyone who ventures a projection, or imagines how a social dynamic, epidemic, war, or migration would unfold is running some model"*.
Modelling is an introspection exercise where you take into account the domain to elaborate a **formal** representation of the conceptualizations you develop around the problem. Mainly, it will have to do with mathematical expressions from calculus or algebra and logics. That is called **conceptual modelling**. This phase comprises the development of a relevant simplification, which must be complete according to the phenomena that inspires the question. Anything left out will change the outcome of the simulation, and non-relevant added items will produce noise that will difficult posterior analisys. All the involved facts must be correctly well grounded taking into account that any unneeded compound in the model will also be added to the scientific and mathematic justification, adding good-for-nothing effort.
For instance, lets consider modelling the dynamics of a restaurant to find an optimum allocation of waiters between interior and terrace tables and their serving policy, so it could be minimized the hired waiters while lowering the waiting time of clients. Variables like client arrival rate, kitchen serving time, number of interior tables, number of terrace tables are reasonable parts of the system to add to the simplification. The colour of the courtains, the outfit of the waiters most probably will not account for the stated optimization objective. Someone could argue about the topology of the tables whether it should be added or not to the model. But if the objective is to model the system to analyze the survival rate when there is a fire and people must exit from the building as soon as possible, table and furniture topology is an unquestionable variable.
This kind of criteria should lead to a preference for simpler models. There are many reasons which force to design consciously with this premise. More complex models require harder effort to work their credibility, verification for the correct implementation of the conceptual model, and from the formal point of view, validation of the model and the scientific conclusions. Considering the system conceptualization and formalization, a more complex model is more open to criticism for the objective or subjective choice of features and modelling decisions. Why the present features were chosen and the missing ones were left out? why one expert point of view, and not other one? Also, as Robinson [21] states, simple models have many advantages, such as they are faster, require less data, are more flexible. But the crucial point is if we better understand them we can better interpret their results. Constituents in models interact each other following the relationships established by the modellers. This produces a network or causality chain that is responsible of the state changes of the model along the simulation. These chains must be inspected to find the origin of the phenomena exhibited in the simulation. As we want to understand a system we must reconstruct the processes that lead to the outcome we observe or check against our assumptions or real world events. If we are designing models where constituents are grouped to conform more complicated constituents, if we design the model to exploit emergent phenomena, analisys of the outcome and the causality chain reconstruction will be

a very difficult task to disentangle [24, p.31]. Simplicity is a must. Besides, we are not aiming at a very rich and complex model that matches its outcomes almost perfectly with some referential real data. As it is explained below we have preference for a model that makes easier the task to explore social processes to answer and propose arising questions. We must find the causal conection between experimental parameters and model dynamics, which parameters under which diferent initial conditions make the system behave differently and say why. Another concern is that detail and granularity choice are attached to the overall direction that takes the construction of the model in terms of structure. At this point it is interesting to mention how does a model can be grown.
According to Oppenheim's and Putnam's[22, p.1-2][23], theories describe their domain as a corpus of interelated concepts where the pieces of knowledge are connected with mathematical, hierarchical, structural and logical relationships, to enumerate some. The hierarchical relationships induce a multilayered organization of knowledge, sometimes called ontology[1]. The hierarchy of layers is related to the level of the abstraction of the contained concepts, going from concrete concepts to abstract ones that contain or subsume the former. Also, the composition relationship makes arise a hierarchy of layers. For instance, in social sciences, considering individuals which are part of families, families which are part of social groups, and groups which conform a society.

Usually, modelling methodology takes either the top, bottom or a midle layer to crystalize the model following the hierarchy in a direction towards the higher concepts or the deeper ones. An ascending crystalization from simpler to more complex is called **bottom-up** and the inverse direction is known as **top-down**. Crystalization could begin in a midle layer and stop before arriving a top or bottom bound layer.
For instance, some simulation would consider a necessity to model individual persons with agents taking decission at that scale. Other simulations would model households with the decission process without having to consider individual persons. Once set this issue, the modelization could keep considering more abstract structures like families or tribes as a composition of households and stop here instead of continuing adding villages or countries to the model.
The point is that the range of concepts that you choose to include in the model is related to the level of detail you want apply to descrive the constituents of the model. The simplest chosen concepts that merge as constituents of other complex constituents and phenomena mark the granularity of your model.

Although good modelling of the parts could be accomplished accurately lefting out the non-relevant entities and phenomena, let's remember the famous quote of George Box, "essentially, all models are wrong, but some are useful" [27, p.2].

By the way, it can also happen that the modelization requires go further the

[1] We are not talking about knowledge representation from A.I.

bound. For instance, consider we are modelling a society to see the emergence of the differentiated groups, in our project, hunters, gatherers, agropastoralists . We could model towns, neighbourhoods, go down to families and then arrive to the person. Maybe we would like to characterize persons with some inner traits related to their personality as anxiety, generosity, aggressiveness, cooperation aptitude. Now we are entering in a layer belonging to psychology sciences, we have surpassed the bottom conceptualization in sociology. If we go further we could arrive to the brain structures entering the field of neurology. We could continue to mollecules, biochemistry, and so on and so forth[28, p.56].
Trespassing these borders and needing the help of experts able to manage and modelize the concepts will be the motivation for multidisciplinarity.

Besides having to cope with implicit ambiguity in each discursive knowledge (as said before, Social Sciences usually represent their knowledge in discursive texts using natural language), all these branches must cooperate in a common framework connecting the different used conceptualizations. Some branches can organize their knowledge in concepts of entities, other use processes or actions, for instance. We cannot collapse this frameworks directly in a formal model. The modelling process will ellicite this structures and will match them with the mathematical tools offered by the chosen paradigm(lets say Dynamical System Theory, Agent Based Models, Petri Nets). We will translate the conceptualizations to a common language that will connect the formalizations in a whole, the **conceptual framework**.
Modelling will help to find a consensus for expressing the concepts and properties, will help to ellicite knowledge, arrange ambiguities, detect common points. It will allow as to embed the needed rigor to work under the same framework to make every part work together. Modelling shall be an exercise of shared development that can approach positions and circle a communication problem to solve the issues that will arise.

2.3 Modelling in social sciences

Social science refers to the academic disciplines concerned with society and human behavior[28, p.7,chap.3].
We will take the point of view where the study of society or social groups considers its target as a adaptative ecosystem of people with interaction, other living entities, environmental conditions or environmental dynamics, information exchange and the mutual adaptative changes induced between the actors, co-evolution [26, p.4].

Modelling societies implies being aware of constituents identified by the social theories. Interacting entities form a society. Such entities are observed and abstracted from identifiable individuals, people, and activity units, for instance families, neighbourhoods or job partners, composed also of the same individuals. An individual leaves a trace of participations and interactions in the society through social processes. Such activities occur with other individuals, with some activity units or through them. Populations of individuals flow through the social structures, selectively participating and differentially performing [29, p.8]. Ordinary living involves a participation of people in the social activities of family, leisure and holidays, shopping, work and travel. These activities within units are structured by relationships and choices, rules, rituals and randomness. Ordinary living also involves the participation of cultural ideas and artefacts in social activities.

Social sciences seek to understand not only how individuals behave under the social influence, but also how the interaction of many individuals leads to large-scale outcomes and global phenomena [29, p.9].
Modelization will be the construction of an **analogy** between these constituents and processes identified by social sciences as elements, procedures, terms or expressions in some **representation language** that allows to manipulate and reason about them.
The main observed issues, individuals, units, processes or actions, flow and dynamics within units, are the frontline of the modelization aspects and motivation for the different paradigms appeared or adapted to solve the modelling objectives. New knowledge to infer from this identified phenomena will be the **descriptive** statement of observed behaviour, quantitative empirical **generalisations**, construction or assesment of **theories** and **prediction** models [30, p.9-53].

The first paradigms to model social processes were borrowed from the fields of physics, operations research, and economics. The first social concepts considered were those related to social units or subgroups and large processes. Also, due to the main use of dynamical systems and differential equations, social phenomena was modelled as a flow between different containers that represent groups or state of individuals.

Richer representations to cope with reality led to nonlinear specifications and the introduction of heterogeneity present in social systems making them hard to represent or analitically unsolvable, hence, the following years saw the spreading of **simulation techniques**, first AI aproximations, cellular automatas and Petri's networks that allowed a finer granularity going from the top abstract groupings infered in social theories to the individual entities[11, chap.1,p.6-9].

Gradually social modelling began to approach computational sciences keeping its connections to mathematics and statistics. Programming languages are more expressive, less abstract than most mathematical techniques. Programs deal more easily with parallel processes and processes without a well-defined order of actions compared to math equations. There is a quite long experience on studying programs and their properties from Algorithmics, Soft Engineering, and Operating

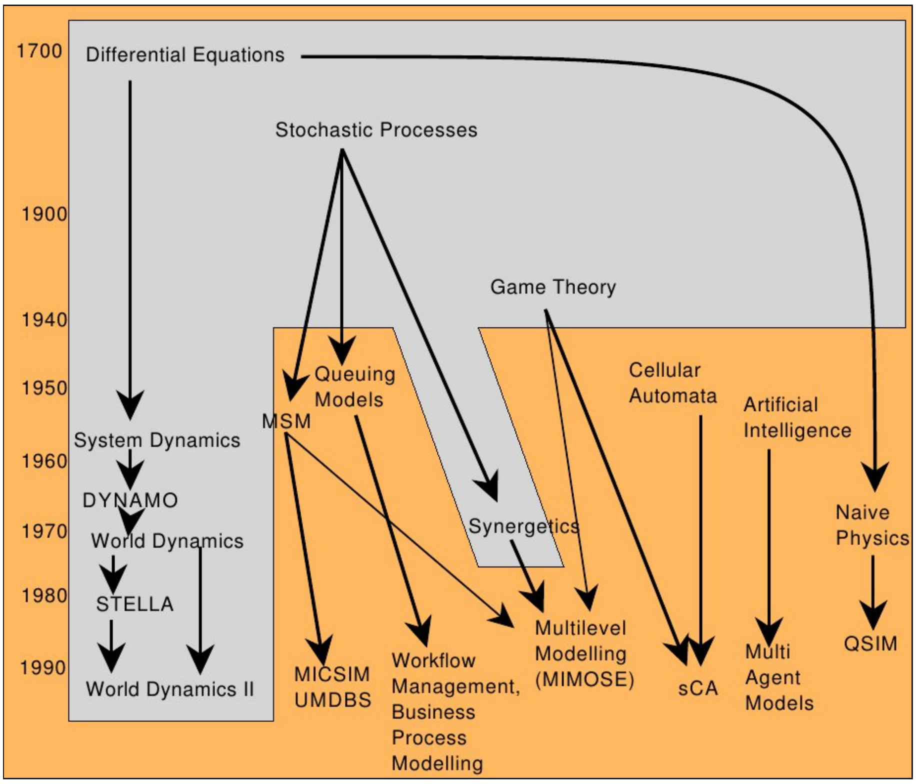


Figure 2.1: The development of the first approaches to simulation in the social sciences (after Troitzsch [11])

Systems. The enginering of big models benefits from these branches endowing them with the desirable properties of modularity, extendibility, the experience of combining programs to grow huge program systems, error detection and maintenance, to mention some [10].

2.3.1 ABMs in Social Modelling

With its strong component from software engineering, considering the ABM(Agent Based Modelling) methodology to be applied to social modelling there are some striking features that make it stand out from other paradigms or approaches. ABM copes with the simple and bottom constituents of social science implicated in the modelization of a system, hence it can sometimes allow to describe a system naturally. It is not easy to develop an agent, but you are working with a metaphor with a structure and concepts that we have at hand everyday. So it is more manageable and natural to express things with that "language" giving more flexibility in the modelization.
The use of ABM in social modelling allowed to introduce the bottom layer of the hierarchy of concepts of social science, **people** and all the package of phenom-

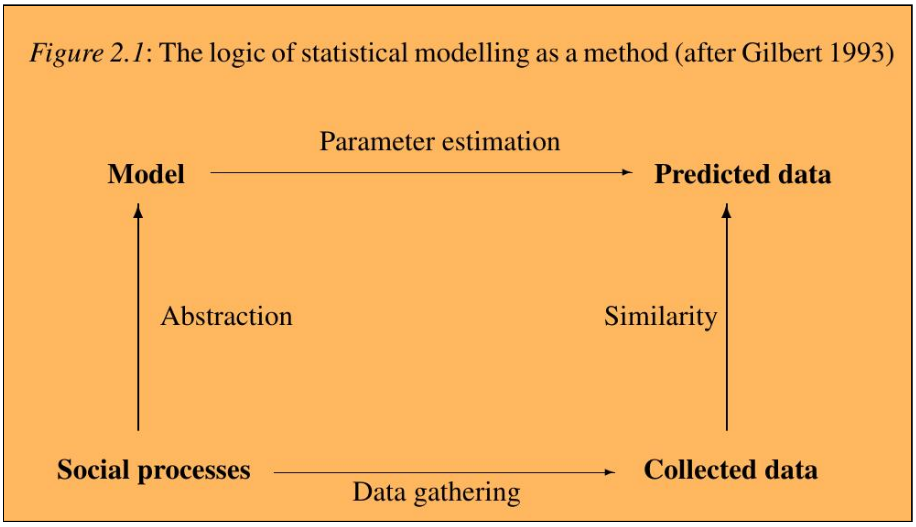


Figure 2.2: The logic of statistical modelling (after Gilbert 1993)[11]

ena and issues associated to it. Once you are modelling a person you can work directly with personal or social relationships and their properties, arity, creation and destruction mechanisms, transitivity and interaction rules. This allows to solve models non solved before, like some cooperation, coordination and competition scenarios from game theory where several agents are involved, for instance. Also the direct interaction and feedback effects between the entities and the environment can be represented in the model. Before this step, other paradigms could not cope with the intrinsic phenomena of people interacting in a social scenario. Different issues had to be modelled that were very difficult or impossible to model with raw mathematics. Social entities, let's say people, or social groups, are not like particles which under the same conditions behave the same way. Two distinguishable entities will act differently under the same conditions. People have different perspectives on their social worlds, have a different knowledge corpus or skills [11, p.19]. ABMs allows the introduction of this heterogeneity in the models, and also embedding of the Rational Choice Theory [12], bounded rationality, and complex cognitive processes. We can give each agent an individualized set of traits, features or methods that will model their different performance in the interactions. We can give them or allow them to catch a different picture from the world, the other agents and themselves.

ABM is most indicated for describing and simulating a system composed of "behavioral" entities. Whether one is attempting to describe a traffic jam, the stock market, voters, or how an organization works, ABM makes the model seem closer to reality. It is more natural to describe how a party of hunters move in a terrain and circle their preys than to come up with the equations that govern the dynamics of the density of hunters. By the way, because the density equations result from the behavior of hunters, the ABM approach will also enable the user to study aggreg-

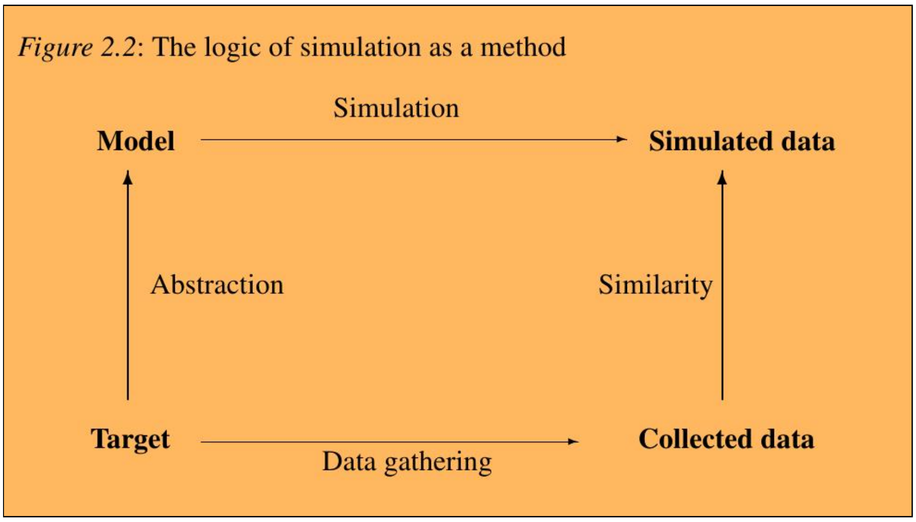


Figure 2.3: The logic of simulation as a method (after Gilbert 1993)[11]

ate properties[36, p.2]; ABM can manage agents at different levels of aggregation. The decission units can be a person but also social entities like families, couples or tribes with their own rules for intearaction and behaviour. You can tune your model easily moving between different layers of abstraction from social sciences. ABM works with models where decission-making and aggregation is clearly separated. The range of complexity of the agent, its behavior, degree of rationality, ability to learn and evolve, and rules of interactions can be tuned more independently of the range of complexity of the aggregation, individualality, and groups. This allows the modeller to work with different levels of description or complexity in the same model[36, p.2].

Also, modelling with agents from a bottom-up point of view will allow to be near the real causes of macroscopic large scale phenomena non predicted from the microscopic local issues. Lets mention an example from Helbing,[38]; consider a fire escape situation in a confined space: a movie theatre or a concert hall. Let us assume that there is one exit available. How can one increase the outflow of people? Narrowing down the problem, one could ask: what is the effect of putting a column (a pillar) just before exit, slightly asymmetrically (for example, to the left of the exit), about 1 m away from the exit? Intuitively, one might think the column will slow down the outflow of people. However, ABM, backed by real-world experiments, indicates that the column regulates the flow, leading to fewer injured people and a significant increase in the flow, especially if one assumes that injured people cannot move and impede the flow. This result is an example of a **counter-intuitive** consequence of an emergent phenomena: who would think of putting a column in front of an emergency exit? ABM captures that emergent phenomenon in a natural way (see table 2.1).

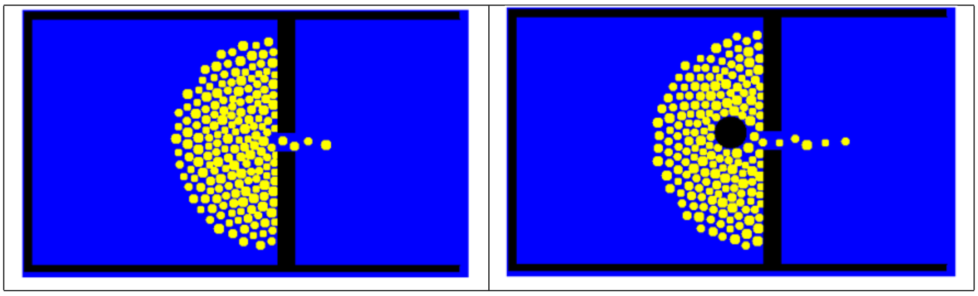


Table 2.1: Unexpected emergence of scape patterns under different situations.

Under the next conditions it is advisable, natural and easier to use ABM.

i- The behavior of individuals cannot be clearly defined through aggregate transition rates.

ii- Individual behavior is complex. Everything can be done with equations, in principle, but the complexity of differential equations increases exponentially as the complexity of behavior increases. Describing complex individual behavior with equations becomes intractable. For instance, the individual copes with hysteresis[2], or there is heterogeneity in the set of behaviours or there are learning procedures and adaptability.

iii- When the interactions between the agents are complex, nonlinear, discontinuous, or discrete (for example, when the behavior of an agent can be altered dramatically, even discontinuously, by other agents).

iv- When space is crucial and the agents' positions are not fixed. Example: fire escape, trade, foraging in a stochastic spatial distribution of resources, traffic.

v- Activities are a more natural way of describing the system than processes.

vi- Validation and calibration of the model through expert judgment is crucial. ABM is often the most appropriate way of describing what is actually happening in the real world, and the experts can easily "connect" to the model and have a feeling of "ownership".

vii- Stochasticity applies to the agents' behavior. With ABM, sources of randomness are applied to the right places as opposed to a noise term added more or less arbitrarily to an aggregate equation.

[2]Hysteresis is the dependence of a system not only on its current environment but also on its past environment. This dependence arises because the system can be in more than one internal state. To predict its future development, either its internal state or its history must be known[46, p.571–597].

A last characteristic feature of agent computing, although not often noted, is that once a model has been created it provides not merely one aspect of the solution — the equilibria, say, or the stability — but rather entire solution trajectories [37].

Issues for ABM applied to social simulation

i- Parameter instantiation

ii- initial population(statistical sampling? emergence & selection?)

iii- initial state of the world at step 0: amount of resources,...

iv- initial state of the agents? age ditribution,...

v- stop event, time bound,... oscilations & attractors...

vi- bounded rationality : agents are not megamachines/superman, they commit erros, have mistakes... Not too perfect decission making is desirable

Epistemology of ABMs in Social Modelling

Considering specifically archeology, the introduction of modelling led to the first use of these models as emulation of reality. ABM was used to reproduce the patterns in the material samples found. This led to think ABM as a way of statitistical distribution fitting. ABM models where thought as models that aproximated stochastic variables and patterns in the model. This was the scientific use of ABM. With the idea of producing more accurate explanations of the phenomena, ABM models began to be filled with more details. The objective was to approach the model to reality to obtain nearer outcomes to the data taken as reference. Those first models were designed to be a mirror of reality, and that is why some experts have been calling them Emulation Models. As it is discused by Premo [24, p.33] this stalled the usability of models, first due to the difficult of interpreting the causality and processes in a simulation experiment that leads to the arising of phenomena, and second, due to the problem of **equifinality** [24, p.31].
The simulation of a model produces a trace of the states visited by the system. If we execute a stochastic model, the states will be conformed by the exhibited values by the model variables following some distribution. That trace is just only one from all possibles that could appear from the combinations that randomness can produce in the variables. Hence, for a single model and an initial configuration, the stochasticity can lead to many different traces although the system finishes at some atractor state or the same patterns arise. The question is, which trace must be taken into account to explain evidences found in reality? This would be an example of equifinality.

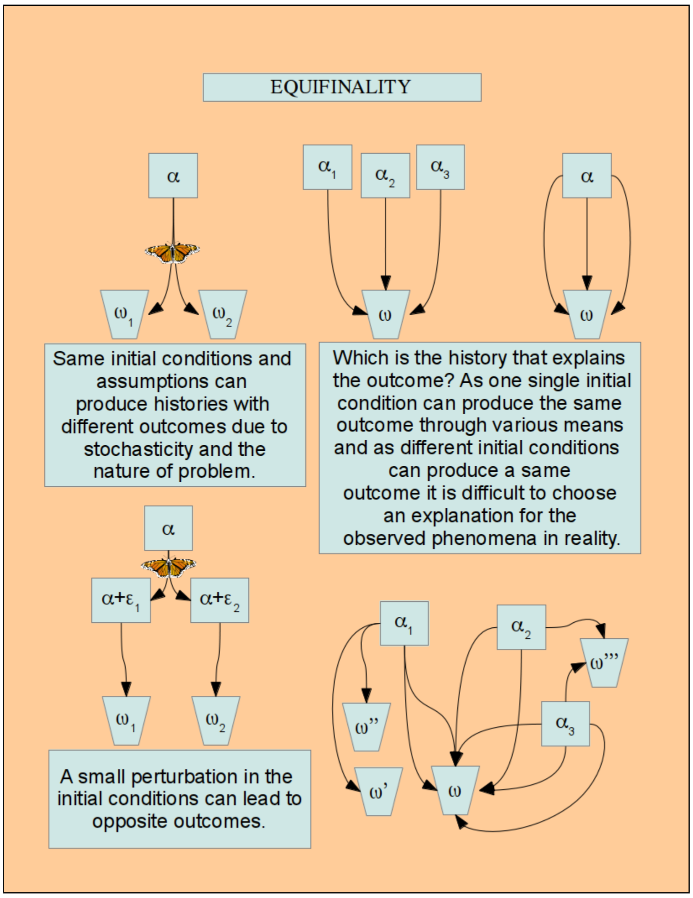


Figure 2.4: Equifinality in stochastic simulation models. For an initial state with its assumptions α a simulation generates a trace of states that lead to a final state or set of patterns and phenomena ω.

There is also equifinality when given different initial conditions or assumptions on the model the same outcome is reached. Which is the initial escenario that produced the evidences? Due to the long time of the history trace, all initial conditions could have the same probability and data does not makes easier the discrimination. Equifinality also appears when the system exhibits sensitivity to initial conditions. Sensitivity is a typical trait of **complex systems** and it is commonly known as the **butterfly effect**. A small perturbation, that is considered **negligible**, in a initial condition can produce a trace with opposite conclusions respect another one without that perturbation. Furthermore, due to sensitivity again, an initial condition in different runs belonging to a same simulation experiment will have usual small perturbations appearing as differences between different traces. Sensitivity to these small inner perturbations can lead to opposite outcomes in the experiment making it difficult to extract and deduce the common patterns or general behaviour we desire to check against data. It will be harder to separate noise from informa-

tion. The same listed issues hold when instead considering several initial states or assumptions we consider diverse models as candidates for the explanation.
There is another alternative to replicating evidence, another way of exploiting ABMs within another epistemological strategy descrived by Premo [24, p.33-34] named **Exploratory Models**. Models can be simplified to the bone. This would keep the most essential processes related to the scientific question that motivated the simulation. As it is said above2.2, a simple model allows a clearer insight of what is happening, and of the path of causality between the constituents and the phenomena. Then, taking advantage of equifinality, the use of the model is to explore causality and tendency in the different traces, how happens the connection between assumptions and parameters with phenomena and states. Simplicity in the model allows to design controlled experiments and very explicit and bounded assumptions for hypothesis generation about the model to enhance the knowledge of the processes we model from reality. Then, these experiments will explore the space of parameters under sensivity to detect ranges, tendencies or configurations that produce patterns similar or far from the empirical observations.
The connection between hypothesis, assumptions and outcomes is studied by the modelers applying **retroductive reasoning**[24, p.34]. Retroductive reasoning, also known as **abduction** is an inference frame that connects effects with its causes in a coherent way with an a-priori theory. The best example to catch the concept is to show it compared to other syllogisms.
Deduction makes explicit the facts that some premises entail through some general rules. Given that *"all human are mortal"* and *"Socrates is a human"* I state that *"Socrates is mortal"*. You could see this as a kind of prediction engine. **Induction** produces the general rules, it is an abstraction inference process. For some set of sampled particular cases x_i I observe both properties, *"x_i is mortal"* and *"x_i is a human"*. Then, I could express this correlation inducing the rule *"all mortals are human"* or *"if someone is mortal then it is a human"*, but as we all have seen flies and ants dying, the statement would cover incorrect cases. The final produced general rule shall be *"all human are mortal"*. Abduction tries to discover the facts that act as cause for some observed evidences. This inference process produces a causal **explanation**. For instance, I find a dead entity e, *"e is mortal"*. I have at hand my a-priori knowledge about the domain, *"all human are mortal"*, and produce my explanation : *"e is mortal"* because *"e is a human"*. That is a plausible explanation, but as shown above, flies and ants are also mortal and it is plausible to say *"e is mortal"* because *"e is an ant"*. Explanation must be refined. Observations and hypothesis trigger new hypothesis to be included in the retroductive inference. New evidences produced by experiments will filter explanations that will allow decide wheter e is a human or an ant. According to Peirce, retroduction can provide good reasons to pursue a hypothesis but does not, by itself, provide good reasons to believe the hypothesis. In successful applications of retroduction, pursuit leads to the accumulation of evidence that will fix the remaining accepted hypothesis for the explanation [25].
The explanation of the outcome and the evidences from reality arises from the as-

semble of the knowledge and evidences we gather from experiments. The model becomes part of a pragmatic reductionism frame, what we comprehend from the inner processes is integrated for the comprehension of the whole. This comprehension will induce new questions and hypothesis (or purge them) that will motivate new experiments and modelling tasks producing a loop of model refinement. Generation of these new hypothesis and questions will also be of profit for theory improvement or theory building and self-criticism in a loop of modelization and question-discovering feeding each other..

2.3.2 Summary checklist

The next checklist sumarizes the steps visited along the process of development and execution of our model. The ABM methodology fits in the the series of defined stages for simulation based research.

Definition of the target A purpose for the model or a question over the target system is stated. The model will be aimed to prediction or prognosis; diagnosis, to construct an explanation for the dynamics or the state of the system; it also can be aimed to theory validation or theory discovering, or study future possible worlds configurations or atractors in the system.

Observations Data gathering, parameters and initial conditions retrieval is done from the target real system using bibliography, interviews and experts' supervision.

Assumptions Relevant simplifications or principal concepts are considered.

Design model Translation of the experts' conceptualizations to a formal modelling language or structure.

Computer programming Implementation of the model in a computational language. A verification phase will test that the program matches the specifications and features of the formal model.

Run simulation Perform the experiments. The runs will generate the traces that will conform the picture of the exploration space for the stochastic variables in the system and the emergent top level phenomena.

Gather results Extract conclussions from the simulation data, stablish correlations and dynamics. This phase will allow to detect evidences for new hypothesis and conclussions or their discarding.

Validation Check that the conclussions are scientifically sound and match the plausible target system behaviour. **Sensivity analisys** will help detect variables and parameters that produce great oscilations on the simulation results and extract issues for the loop of model, theory and hypothesis refinement.

2.4 Conceptual Framework

This section introduces some definitions and explanations about the main needed concepts to expose the design of the model for the issues and questions stated in chapter one. The text begins explaining what agents consist on. The description of agents from AI covers their architecture and competences, and how different techniques and paradigms endow them with the diverse features and capabilities to solve the problems they are programmed for. An explanation about complex systems follows the section of multi agent systems. It is a necessity due to the nature of the problem and the properties exhibited by models consisting in multiple agents interacting each other. The section links typical complex system phenomena to the arising properties of the models studied for the topics of these master thesis. Emergence is defined and stressed in a dedicated subsection. This part finishes giving some brief ideas about what evolution is. The topic is introduced due to the evolutive component in the model to be run in the simulations. We seek to observe how either of the strategies adapts to the changing environment and how the dynamics favors one instead of the other producing adaptative changes in the agents. As we will study the different social groups in a competitive environment the section will introduce the concept of coevolution, the mutual feedback of evolutive changes between neighbour adaptative groups of entities.After this definitions the next part will retake the topic of agents in the section about Agent Base Models to introduce more ideas and issues from Multi Agent Systems and social simulation.

2.4.1 Multi Agent Systems

Multi Agent System(MAS) is an architecture for software development based on designing a solution for a problem that executes of a set of computational entities called agents that interact themselves in a defined environment[13, chapter.1].
Such entities are active decission making actors in the modelled system. The modelling lifecycle of an MAS will consider a stage where decission making processes must be identified from the system. Usually those decission making actions are carried along by more or less clear individual entities from the system. The modelling process will take the task to set the matching between these entities and the agent that will form the MAS. The concept ”agent“ condenses a set of features that will specify the modelling metaphor that an agent represents: some enclosed set of mechanisms to be aware of the state of the system, a set of goals to accomplish and the engine to decide from a bounded perception of the world, the actions to apply on it to achieve these goals. Besides the reasoning component of the agents, MASs have a strong component of inter-agent relationship. How one agent interacts with other agents could as important or more as how it reacts to world changes.

Agents

An agent is a computer system that is capable of independent action on behalf of its user or owner, figuring out what needs to be done to satisfy design objectives, rather than constantly being told.[13, ch.1] An agent solves problems applying iteratively the schema of sense, decide and act continously. Each of the steps can add new targets to fulfill which will keep the agent exploring the environment and interacting with it and other agents to develop its strategies to solve the tasks and achieve goals.

Agents are [14, p.115-152]:

i- clearly identifiable problem solving entities with well-defined boundaries and interfaces;

ii- situated (embedded) in a particular environment—they receive inputs related to the state of their environment through sensors and they act on the environment through effectors;

iii- designed to fulfill a specific purpose—they have particular objectives (goals) to achieve;

iv- autonomous—they have control both over their internal state and over their own behaviour;

v- capable of exhibiting flexible problem solving behaviour in pursuit of their design objectives—they need to be both reactive (able to respond in a timely fashion to changes that occur in their environment) and reactive (able to act in anticipation of future goals).

An example of a very simple agent would be a thermostat. It samples the environment with a probe/sensor, checks if the temperature corresponds to the desired one. According to the measure it launches one of the two actions, to set the heater to ON or to OFF.
But we could have something as complex as an agent representing a car in a traffic simulation while drives from one point to another in the city. The agent would have accesible a knowledge base of traffic rules constraining its actions. The agent at each time step of the simulation would control the swarm of other vehicles to avoid collisions and would follow paths and perform actions coherent to the rules of traffic. The traffic rules would act as middle interface consensus of fair driving that coordinates all the cars and allows some prediction of the adjacent cars. The agent can be designed a step further. When congestion increases to a predefined threshold, which could be tuned through authomatic learning, the agent recalculates the route to adapt and avoid the traffic jam.
Intelligent agent design considers the setting of Perceptions, Actions, Goals and Environment. These aspects form a general structure where an agent design can

grow. Mentioning an example considering a system that simulates hunting practices from ancient cultures will show how features from the agent are attached to these modules in the structure(table 2.2).

Perceptions	Hunger, TerrainSlope, ReadTracks, LookForPrey.
Actions	Eat, LightFire, Cook, ThrowArrow, Walk, Run, Stalk, Hide.
Goals	Survive, AvoidHarm.
Environment	Weather, Plants, Mountain, Valley, Caves, Deers, Rabbits.

Table 2.2: Setting table for a hunter agent.

Agent brief formal description Let E be an environment with a finite set of states

$$\Omega = \{\omega_0, \omega_1, \ldots\} \tag{2.1}$$

Each agent has available a set of actions

$$A = \{\alpha_0, \alpha_1, \ldots\} \tag{2.2}$$

An action is a function that changes the state of the environment

$$\alpha_i : \Omega \longrightarrow \Omega \tag{2.3}$$

An agent's run is a sequence of states of the environment where the transitions were triggered by actions launched by the agent. Let R be the set of all possible runs over Ω and A, and r^u one sequence of length u.

$$r^u = (\omega_0, \alpha_0, \omega_1, \alpha_1, \ldots, \omega_{u-1}, \alpha_{u-1}, \omega_u) \tag{2.4}$$

Let R^A the sequences that end with an action

$$r_A^{u-1} = (\omega_0, \alpha_0, \omega_1, \alpha_1, \ldots, \omega_{u-1}, \alpha_{u-1}) \tag{2.5}$$

Let R^Ω the sequences that end with an environment state

$$r_\Omega^u = (\omega_0, \alpha_0, \omega_1, \alpha_1, \ldots, \omega_{u-1}, \alpha_{u-1}, \omega_u) \tag{2.6}$$

Actions in the run are the response of an agent X_i to the states of the environment

$$\forall j \in [0..u-1] : X_i(r_\Omega^j) = \alpha_j \tag{2.7}$$

An stochastic and historic dependent environment behaviour, τ, can be described as

$$\tau : R^A \longrightarrow \wp(\Omega) \tag{2.8}$$

A Markovian environment behaviour would be defined as

$$\tau : \Omega, A \longrightarrow \wp(\Omega) \tag{2.9}$$

and the next would hold for the runs

$$\forall i \in [0..u-1] : \tau(\omega_i, \alpha_i) = \omega_{i+1} \tag{2.10}$$

Let's say that no end condition is described for the runs here because althought it could happen $\tau(\omega_i, \alpha_i) = \varnothing$, many other conditions could mark the end of a run. For instance, a run can finish because the population of agents reaches 0 due to some dying process. A run can also stop after a finite number of transitions, or some predefined event appears.

An agent X_i retrieves information from the history of environment states to choose an action to launch

$$X_i : R^{\Omega} \longrightarrow A \tag{2.11}$$

Agent Main Behaviours There is a set of key points that an agent should accomplish to go beyond a simple AI application, a problem solver, or just a system process. AI has compiled some asked mandatory behaviours lisked below to a software to be considered an agent [13, ch.2][7, ch.1, ch.2].

Autonomy Other entities do not set the agent objectives nor decissions. With agents, we give a high-level description of the delegated goal, and let the control mechanism figure out what to do, knowing that it will act in accordance with some built-in theory of rational agency to satisfy it.

Reactivity Response to environment stimulus or changes. A reactive agent is one that maintains an ongoing interaction with its environment, and responds to changes that occur in it (in time for the response to be useful). A pure reactive agent, the thermostat can be formally descrived as

$$X_i : \Omega \longrightarrow A \tag{2.12}$$

Proactivity It means anticipation, taking initiative, detect oportunities. This could materialize in prediction of a future event an realize a set of a priori actions before it occurs. For instance, if you are modelling a population of farmers and agent A1 sees the state of low resources of its neighbour agent A2 at the end of the season. As a social action, A1 makes a pressent of food to A2 before it begins to starve or asks for help. We also know that this kind of action will produce stronger bonds and could have their pay-off in the future. But the most extended example is when you enter in a bookshop, as you delay a bit in your search, a salesman appears offering its help before you ask for it. It could mean that the agent produces a set of actions that trigger an environment event that will allow the execution of an action the approaches the agent to its goals.

Social capabilities Cooperation, coordination, negotiation, competition, and mind models. Some objectives are not achievable by the only means of the agent. The agent must interact with other entities that can produce the chain of actions to produce the changes in the environment needed. Agents inhabit and intearact with the environment applying actions and producing effects in a same medium. Goals, effects and dynamics can clash. Is it possible the appearance of conflict. Goals and planned trend can be contradictory for more than one agent. According to the model of negotiation of the agent it can try to change its plan trying to not interfere with the other agents, or produce a deliberate interference or ignore it and stick to its objectives. Social capabilities will cover the spectrum of comunication but also integrate the other agents behaviour. Some sophisticated agents include mind models to add, predict the other agents' behaviour in its knowledge representation engines.

Cooperation Cooperation is working together as a team to achieve a shared goal. Often prompted either by the fact that no one agent can achieve the goal alone, or that cooperation will obtain a better result (e.g., get result faster). That is very easy exemplified with hunt parties or some families of farmers that while one member takes care of the plot the other takes the cattle for grazing.

Coordination Coordination is managing the interdependencies between activities. For example, if there is a non-sharable resource that you want to use and I want to use, then we need to coordinate.

Negotiation Negotiation is the ability to reach agreements on matters of common interest. At the appearance of conflict a solution that benefits the parts is searched. For example: Two farmers arrive at a piece of land good for crop growing. A possible deal: split the land in two.Another solution : both work on the land, but each has assigned different tasks. By the end of the year they divide the harvest. Typically involves offer and counter-offer, with compromises made by participants.

Learning Prediction for future situations,reuse solutions,avoid past errors. The agents stores patterns from the history of environment changes, or other agents' actions. The patterns induce a model of the world or of the task to perform used by the agent for future actions. As a detail, although the learning could be produced in first stages of the run to produce benefits along the life of the agent, it is desirable that the learning should occur along all the run to produce a real adaptation of the agent. The keyword is **incremental learning**.

Intelligent Agents Architecture This paragraph will show different decompositions of how an agent is structured and provide an answer to the question of how the sensor data and the current internal state of the agent determine the actions and future internal state of the agent. The thermostat example contains an environment with a bounded and tractable number of states. Such situations can be solved with a direct implementation setting the bijective function state - action with a table or with a limited number of rules. As complexity of modelled systems grows, the number of states and possibilities become untractable. Theres no time nor space to specify each correspondence. The agents apply different techniques for retrieving features and structure from the environment to proceed with the decission process from an abstraction to the action to perform [7, ch.2].

Reactive Architectures

The decission process in Reactive Architectures selects actions only based on the last perception retrieved from the environment. It does not considers any subset of past perceptions. Reactive Architectures encompass the Simple Reflex Agents.

A change in the environment provokes a response from the agent. When changes and deliberations in agent are only motivated by an event in the environment, the agent is pure reactive.

while *true* **do**
  $\sigma \leftarrow$ getNextPercept();
  $rule \leftarrow$ ruleMatch($rules$, σ);
  $\alpha \leftarrow$ ruleAction($rule$);
  execute(α);
end

Algorithm 1: Simple Reflex Agent main loop

- Cognitive Maps
- State Transition Machines
- if-then rules

Deliberative Architectures

A deliberative agent uses symbolic reasoning to deduce the action to launch. The deliberative agent contains explicitly the goal that steers its behaviour. Deliberation is done through an internal formal representation of the state of the world, the state of the agent and other information retrieved by it. A logic engine will produce deductions from the facts stored in the agent memory, the knowledge base. The perceptions from the environment become facts to add to the internal representation of the environment. From this internal world model the agent can deduce trends for prediction besides the next action to launch. A state of the environment or of the agent is specified. The agent must find the way to fulfill this within his reach of perceptions and actions. Desirable situations are seeked, called goals, that is environment states or agent states.

Given some systems or situations, goals are non achievable from a single action execution. The agent must apply search and planning techniques to conform a plan that will satisfy, after a limited number of steps, the desired goal.

Goals could be a design feature of the agent, for instance **survive** & **reproduce**, or could be set dynamically in runtime by conditions in the environment or through user commandment.

Logic Deliberative agents will use assert clauses and structures to represent facts in a logic of some level, CP0, CP1. Each new change in the knowledge base will allow to deduce new facts from the status of the system to check againts the goals and other issues the agent is considering to produce an action coherent with the planning and the mechanics of the environment to fulfill a new step to get nearer to the goals. The agent will use its knowledge base as a theory of the world and things plus the dynamic facts that represent the volatile states.
Let ρ be a theory of the world. Depending on the architecture this can be a set of rules, or a learned structure along the run.
If Γ is a description for the current state of the world. A the set of possible actions $\{\alpha_1, \alpha_2, \alpha_3, \dots\}$. And $\Gamma \vdash_\rho \Phi$ stands for a succesful prove that Φ is deduced from the knowledge base Γ using theory ρ. The Deliberative agent will choose actions according to a schema like that:

forall the $\alpha \in A$ **do**
  if $\Gamma \vdash_\rho doAction(\alpha)$ **then**
    return α;
  end
end
forall the $\alpha \in A$ **do**
  if $\Gamma \nvdash_\rho \neg doAction(\alpha)$ **then**
    return α;
  end
end
return null;

Asserts from Logic will be used to state the facts that are true from environment and the other agents.

BDI BDI stands for Belief-Desire-Intention. Yoav Shoham introduced “agent-oriented programming” in 1990 [16]:“new programming paradigm, based on a societal view of computation”. The key idea is about directly programming agents in terms of **intentional** notions like belief, commitment, and intention. Beliefs are used to model the state of the world.

Desire allows the selection of possible states of the world and preferences. Intentions are compromises to achieve a given state, they are the commitment of the agent.

BDI belongs to a overloaded kind of logics called modal logics which add meta language operators to the facts to alter with some nuance the meaning or the semantic interpretation of the fact. For instance, let ϕ be a fact that could represent "deer is in the wood". Indeed it is true for the example. Our agent has not seen it and only has some clue that the deer is in the wood; so the agent states $\Box_B \phi$, with an operator $\Box_B$ to indicate "I believe the deer is in the wood". The memory of the agent will contain also the facts below

θ = "I am hungry".

η = "I go hunting".

$\Box_D \eta$ = "I have Desire for going hunting".

$\Box_I \eta$ = "I have Intention for going hunting".

Some of these entail from other. They are governed by the next rules from the knowledge base

- myState(HUNGRY) $\rightarrow \Box_D$ doAction(HUNT)
- $\Box_D$ doAction(HUNT) $\wedge \Box_B$ entityAtPlace(x,y) $\wedge$ edible(x) $\rightarrow \Box_I$ doAction(HUNT)
- $\Box_I$ doAction(HUNT) $\wedge \Box_B$ entityAtPlace(x,y) $\wedge$ edible(x) $\rightarrow$ doAction(go, y)
- entityAtPlace(MYSELF,p) $\wedge \Box_I$ doAction(HUNT) $\wedge$ entityAtPlace(x,y) $\wedge$ edible(x) $\wedge$ distance(p,y) $\leq$ HUNTDISTANCE $\rightarrow$ doAction(HUNT,x)
- doAction(a,x) $\rightarrow$ launchAction(a(x))

This rules would carry the agent to satisfy the goal of feeding going through the goal of going where the prey is, and see that it is indeed there where the agent believed.

Programming agents this way allows a deeper description of the dynamics around the goals an agent self-imposes and also an easier way for the agent to reason about the other agents. This last point is crucial for a better integration of the social dynamics in the planning of goal achieving. The agent can construct through facts of Believing, Desire and Intention a mind model of the other models taking into account their BDI intentions and adapting to them to cooperate or compete.

Continuing the example, the agent would be inmersed in social deliberations after retrieving from the world facts like $\Box_I^i \eta$ that stand for "Agent i has the Intention of hunting". The interaction of all these facts, entityAtPlace(MYSELF,P), entityAtPlace(i, P) will make deduce to the MYSELF agent somekind of communication protocol with agent i to solve the conflict. Because they could end to hunting the same deer,

before they would launch their HUNT action, they must reach a consensus about what to do each other.
Schema for BDI

$B \leftarrow B_0$;
$I \leftarrow I_0$;
while *true* **do**
  $\delta \leftarrow$ getNextPercept();
  $B \leftarrow$ brf(B, δ);
  $D \leftarrow$ options(B, I);
  $I \leftarrow$ filter(B, D, I);
  $\pi \leftarrow$ plan(B, I);
  execute(π);
end

Algorithm 2: BDI main loop

Utility based Goal-based models are a dycothomic approach that rely on bivalued logics. A goal is considered achievable or not achievable, an agent is commited to a goal or is not commited to that goal. But many fields have shown things usually work in a fuzzy manner or probabilistically or with multivalued assignations. Mentioning some example, robot soccers. In a match, eventually, you could pass the ball to a partner or try to score. If you launch the action “pass” things will happen different from launching action “score” but a priori you cannot predict which will be of more help. And if you stop to think about it the opponent will steal the ball from you. Another example, a fire simulation. There are many escape routes; when a route is saturated due to congestion, people have a variable internal timeout wait time to leave the route and try another one. There is also fuzzy phenomena in auctions; auction agents have to decide wheter raise the “bet” or leave.

An agent under these circumstances will find a set of available goals where each one produce a different benefit for the agent itself. The goals, the states of agent and environment must be weighted in function of probability of success, or benefit for the agent. Also, there is some related optimization trend or related likelihood of achieving positive results.

A pure logical agent can find a cul-de-sac on its deductions if the possible contingencies overcome the reasoning to deduce the actions to fulfill the goal. These issues are what is called **uncertainty**. Uncertainty is the term used when there are many solutions that lead to the goal or if the goal is something not sure to be achieved and the agent faces a choice with no success ensured.

For instance, considering a hunter agent in a social simulation of ancient societies, a hunt action can be affected by many issues. First you must make a guess about where the preys are. Once you begin

the hunting session many things could happen: a weather incident that changes prey grace behaviour, other hunters appear to hunt the preys, or dangerous roaming predators. The pure bivalued logic agent cannot predict the setbacks so cannot deduce the sucess of the action, and the hunt action will not be launched leading to starvation. If all the logical paths towards the achievement of the goal are troubled by contingencies, the agent could fall in a loop of inactivity.
When perfect solution is perhaps non achievable, the agent should be allowed to satisfy the goals through a non perfect solution. The decission engine should be changed to accept failable solutions for its goal seeking. Another hunt area should be eligible in the decission process. But maybe, although the other area is free of contingencies, it cannot offer a good outcome because is almost dessertic. Someway the agent should express a **preference** and deduce the action planning according to it. Preference over the outcomes of and action in the goal seeking activities of the agent encompass the modelling of success probability and benefit quantification. A particular outcome should be the fact that the hunter returned home without getting injured and a certain amount of Kg. of meat.
Utility theory is used to represent and reason with preferences. Utility theory says that every state has a degree of usefulness, or utility, to an agent and that the agent will prefer states with higher utility [7]. Preference and similar issues are modelled through **utility functions**.

$$u \,:\, E \rightarrow \mathbb{R} \tag{2.13}$$

Utility functions map desired states to a quantitative dimension, a scoring. Utility ponderation allows to break ties in sub-goal selection. Utility functions will give extra heuristic information about the likelihood achieving a goal. If the hunter agent has acces to two areas of hunting, *valley* and *wood* and is more likely to find dangerous predators in the *wood* although the same preys can be found on both areas, the utility function would assign greater utility to the *valley*. Utility provides a way in which the likelihood of success can be weighted against the importance of the goals.
Preferences, as expressed with utility functions, are combined with probabilities in the general theory of rational decisions called **decision theory**: [7]

$$Decision\ theory = probability\ theory \;+\; utility\ theory. \tag{2.14}$$

Utility-based agents are rational and follow the principle of **Maximum Expected Utility (MEU)**: *An agent is* ***rational*** *if and only if it chooses the action that yields the highest expected utility, averaged over all the possible outcomes of the action.*[7].

Environment Features The design of the agent is conditionated by what is considered "the environment" in the real system to model. It will facilitate or constraint the features and decisions in the development of the agent. Next, some common features that will guide in the characterization of the environment are enumerated [7, section 2.3].

Accessible vs Inaccessible An accessible environment is one in which the agent can obtain complete, accurate, up-to-date information about the environment's state. Most moderately complex environments (including, for example, the everyday physical world) are inaccessible.
The more accessible an environment is, the simpler it is to build agents to operate in it. Accuracy and completeness about information retrieved is key to decission making. All the missing stretch must be supplied with uncertainty managing techniques.

Deterministic vs non-Deterministic As we have already mentioned, a deterministic environment is one in which any action has a single guaranteed effect — there is no uncertainty about the state that will result from performing an action. The physical world can to all intents and purposes be regarded as non-deterministic. Non-deterministic environments present greater problems for the agent designer.

Episodic vs non-Episodic In an episodic environment, the performance of an agent is dependent on a number of discrete episodes, with no link between the performance of an agent in different scenarios. Episodic environments are simpler from the agent developer's perspective because the agent can decide what action to perform based only on the current episode — it need not reason about the interactions between this and future episodes.

Static vs Dynamic A static environment is one that can be assumed to remain unchanged except by the performance of actions by the agent. A dynamic environment is one that has other processes operating on it, and which hence changes in ways beyond the agent's control. The physical world is a highly dynamic environment.

Discrete vs Continuous An environment is discrete if there are a fixed, finite number of actions and percepts in it. Russell and Norvig give a chess game as an example of a discrete environment, and taxi driving as an example of a continuous one.

2.4.2 Complex Systems

Complexity is a discipline that studies systems that cannot be studied through the analisys of its parts and the simple composition of those analisys. Usually, **reductionism** has coped with complicated systems where the supression of constituents

Task Environment	Observable	Deterministic	Episodic	Static	Discrete	Agents
Crossword puzzle	Fully	Deterministic	Sequential	Static	Discrete	Single
Chess with a clock	Fully	Strategic	Sequential	Semi	Discrete	Multi
Poker	Partially	Stochastic	Sequential	Static	Discrete	Multi
Backgammon	Fully	Stochastic	Sequential	Static	Discrete	Multi
Taxi driving	Partially	Stochastic	Sequential	Dynamic	Continuons	Multi
Medical diagnosis	Partially	Stochastic	Sequential	Dynamic	Continuous	Single
Image-analysis	Fully	Deterministic	Episodic	Semi	Continuous	Single
Part-picking robot	Partially	Stochastic	Episodic	Dynamic	Continuous	Single
Refinery controller	Partially	Stochastic	Sequential	Dynamic	Continuous	Single
Interactive English tutor	Partially	Stochastic	Sequential	Dynamic	Discrete	Multi

Table 2.3: Examples of task environments and their characteristics.

does not change the main trend of its behaviour, and it is used to work with simplified questions. Let's think for instance in a car which more or less keeps running although you remove its seats, the doors, and the lights, to mention some. That is what could be called a complicated system [41]. There are systems where the interrelationship is so rich that supression of one part dismembers all the coherence of the system. Taking again the car exemple, if we think about the engine, the suppression of a most tiny gear will change the things, everything will stop. Historically, those systems have been an issue that was of concern to many disciplines, Economics, Physics and Biological sciences, that gave arise through an interdisciplinary effort to complexity science [3] [39]. Complex science tries to find out how the interactions of a set of constituents build a system that exhibits adaptive traits, descentralized organization, and macroscale behaviour patterns.

One of the most known systems studied by its complexity are ant colonies. The colony is formed by a limited range of roles, a queen, soldiers and workers/explorers. Each role exhibits a limited spectrum of behaviours activated by pheromones or stimulus from the environment. Soldiers attack anything that moves non impregnated by the odor of the nest. Unloaded workers follow explorer's pheromons. When food is found a worker returns home. Dead bodies or garbage found are put near other garbage, generating dump patterns. More or less this is the program of ants. And this executed by a huge amount of ants produces an ant colony that manages food resources, reproduction and care, defense and many other adaptations to the wild life in the forest. It can loose part of its population, can balance workload, a same specific individual group of ants is not needed for an especific task. The colony is ductile, malleable. The ant colony acts has a whole with very rich global behaviours. That is a complex system.

[3] here we are not talking about the computational concept of algorithm complexity.

Researchers observed that woods under a fire dissappear at different rates not completely dependent to the intensity of the focus, nor the climatic conditions. It was observed that under some tree topologies and certain wood density a small change in the number of trees would mean sometimes the complete combustion of all the wood, and other times the wood would only burn in a small controlled area. This topology dependant condition is called **percolation**. It arises from the spatial relationship between the trees. Considering an ideal situation where topology protects the wood from percolation appearance, slight changes in some trees distribution will make them sensible to fire, but the rest of the wood will not burn. These conditions are an example of robustness in complex systems. But enough changes will collapse it.
The strong relationships that give arise to the complex phenomena act as the glue that holds the system, it gives reason to the system existence.
Percolation was not discovered studying one tree. It was detected taking into account the whole of the wood and the feedback versus the individual trees.

Indeed we observe that there is a system due to the pressence of the macro phenomena. It is the evidence that something is happening there that relates the constituents.

Just to give a compact definition from Melanie Mitchel [39], "a complex system is a system in which large networks of components with no central control and simple rules of operation give rise to complex collective behaviour, sophisticated information processing, and adaptation via learning or evolution. Sumarizing, a complex system exhibits nontrivial emergent and self-organizing behaviors".

The laws that describe its behaviour are qualitatively different from those that govern its individual units. The advances of computational techniques for scientific discovering is changing the way we confront the models and the manipulation of these issues. Computers have allowed new ways of learning about them. Computational techniques allow the modelling of many constituents and its relationships, how they assemble to a whole system. It allows us to understand and play with the experimental manipulation of the behaviour in a easier way. Computers not only help us in studying the surface of the behavioral phenomena but also the internals of complex systems giving insight to our explanations and deductions. Besides, computational experimentation has the advantage of controlling the trace and generating rich databases of events for posterior analyses [42].

Complex behaviour is tied to a non central global decission process. But, on the other hand, the emerged pattern is something that does not belongs to a identifiable constituent. It is build from the descentralized dynamic of all the constituents. That feature is called **emergence**.

2.4.3 Emergence

Emergence is a phenomenon where aggregation of individual and local behaviours are the direct cause of a higher level pattern or global behaviour. Emergence is one of the key concepts from Complexity that is studied in Social Simulation. Indeed, emergence is one of the main features exhibited by complex systems.[41]

Although we can give features and descriptions, emergence cannot be fully specified due to the vague concepts of "surprising" and non deducibility [40] . But some signals can be enumerated to circle the concept of emergence.

A phenomenon will be considered emergent when it is repeatable and surprising, non deducible from lower level rules and the relationships of basic constituents of the system. Emergence cannot be predicted, given our current means, from only the constituents and their addition, following the reverse way of reductionism. Reductionism is one of paradigms of science. A system is observed to detect differentiated parts. Then each part is analized to extract its behaviour. Reductionism states that the behaviour of the system can be understood from the constituents specifications plus a simple or direct aggregation step. This idea can be applied recursively on the same constituents till some atomic element considered the bottom of the process. The thing is that due to nonlinear relationships, following the inverse path to reconstruct a sense for the whole system is practically impossible.

Even a small and simple set of rules can make a dynamic system generate emergent phenomena. If these rules induce non linear relationships the proportion of a perturbation in the system will not be paired with the response of it. To use an uninventive example, nonlinear emergence occurs when someone **calmly** says "fire" in a crowded room and produces **explosive** panic. Unpredictable results arise from constituents interactions. It is here where emergence can appear. When a pattern is recognizable and repeats usually along experiments, is plausible to be considered emergent [40].

There is potential for emergent phenomena, i.e., when:

- Agent behaviour is non linear (weight sum of variables), or is expressed with discontinuities, if-then rules in a categorical framework or in discrete non continous manner.
- Under memory phenomena, path-dependence, and hysteresis, non-markovian behavior, or temporal correlations, including learning and adaptation.
- Heterogeneous interactions between agents.
- When there is unstability to perturbations although the system could be defined linearly.

2.4.4 Evolution

Evolution theory is the result of observations along several years made by Charles Darwin in his trips to Galapagos Islands and the study of native species of finche birds.

Darwin proposed that the varieties and specializations of observed species was imposed by the topology of the island and the local conditions of each one. The theory arised from the following points in conjunction of the observations. He based his deductions on the next hypothesis:

- Gradual change over long periods can produce very large effects.
- Population growth combined with limited resources creates a struggle for existence.
- Collections of individuals acting in self-interested ways produce global benefit.
- Life seems to allow almost infinite variation, and a species' particular traits seem designed for the very environment in which the species lives.
- Species branch out from common ancestors.

Darwin called **Evolution by Natural Selection** to the improvement by mutation and competition process where individual beings produce offspring at a rate greater of the survival rate (otherwise they would extinct). The offspring is almost equal to the parents except from slight variations. At some point the population will saturate the niche and they will compete for the resources. The more adapted individuals are considered those who will satisfy their resource needs and have higher reproduction success. This will imply that a great number of offspring that inherited features from their successful parents will populate the environment. These traits will persist through the time from generation to generation. This would explain why individuals are as they are and not other way. Adaptation comes from the small perturbations or changes between parents and offspring. This is an open door to the appearance of an improved trait that would increase the adaptation of the new generation. Hence, change after change the Evolution sculpts step by step the organic beings making them more adapted to the environment. Traits that does not allow to survive nor reproduce will not appear in the next generation, except due to some rare mutation but that will be purged again in the competition game against the environment.

To summarize the major ideas of Darwin's theory:

- Evolution has occurred; that is, all species descend from a common ancestor. The history of life is a branching tree of species.

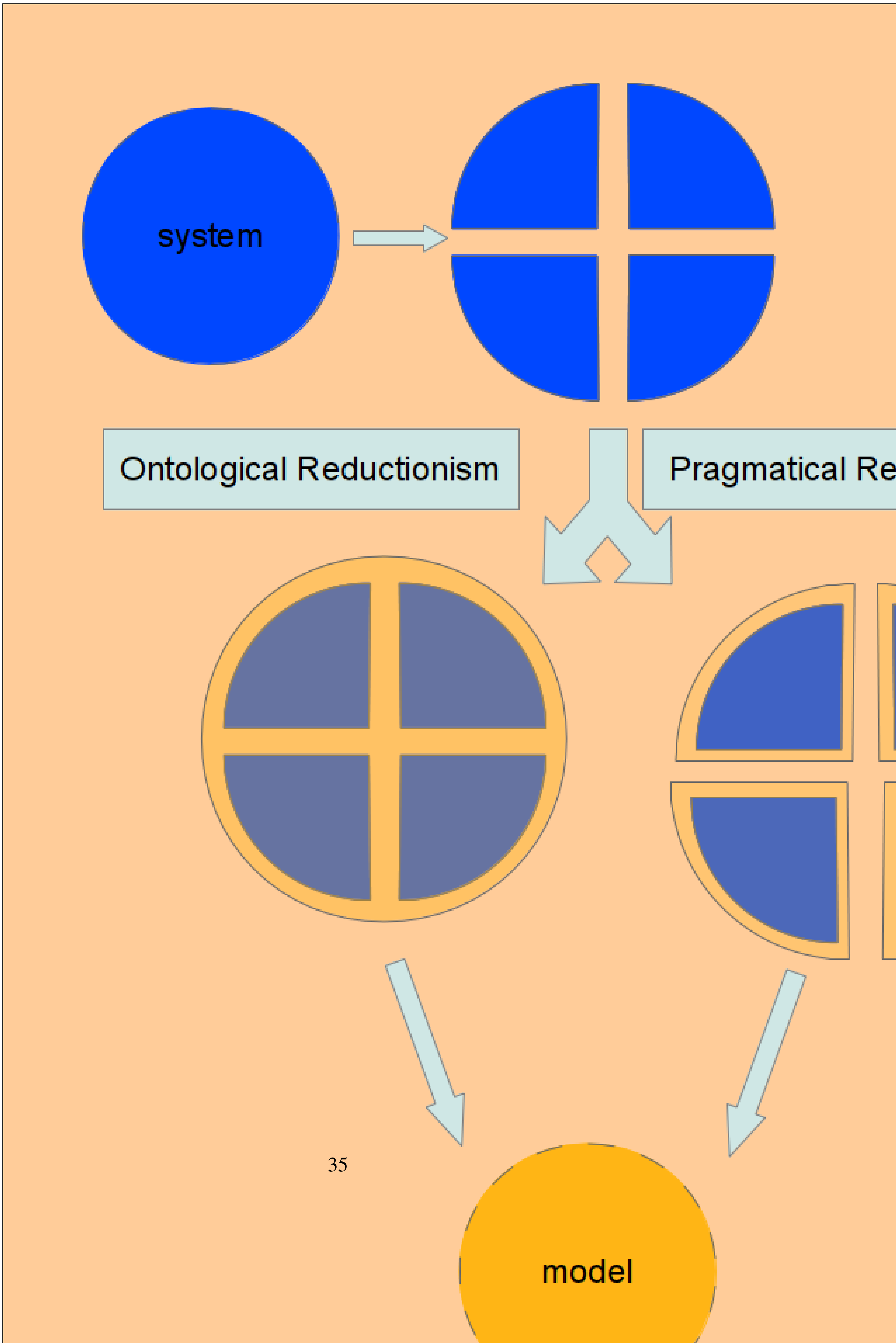
- Natural selection occurs when the number of births is greater than existing resources can support so that individuals undergo competition for resources.
- Traits of organisms are inherited with variation. The variation is in some sense random—that is, there is no force or bias leading to variations that increase fitness. Variations that turn out to be adaptive in the current environment are likely to be selected, meaning that organisms with those variations are more likely to survive and thus pass on the new traits to their offspring, causing the number of organisms with those traits to increase over subsequent generations.
- Evolutionary change is constant and gradual via the accumulation of small, favorable variations.

Darwin theory had some points to be clarified. How did parents pass their traits to the offspring? The process of refining these theories comprised the addition of Mendel's theories lasting till the past century where everything was unified with the descovering of DNA and genomics. DNA is the way in which are encoded the traits that the organic being will probably exhibit in his life, and also DNA is the transmission medium of the traits in the reproduction process. We will take **Richard Dawkins** position as our final work metaphor for evolution and natural selection[45].
As it is mentioned, part of the working framework of our simulation is based on the ideas of evolution and "natural selection". We understand "natural selection" as a process that "rewards" adaptive solutions and penalizes those less adapted. Darwinian Evolution is the result of the continued application of this screening and the persistence of adaptive patterns and what comes off of them. Persistence is produced through the reproductive process of agents. Regularly an agent generates a copy of itself with some disturbance in their features and takes charge of it for a period of time. The extraction capacity of system resources, adaptability, marks their survival and that of their offspring. If the offspring survives, the configuration is maintained over time and gets another chance to be perpetuated when this new generation begets his sons / daughters. We use evolution as a tool for selection of configurations to respond more adaptively than others, working with the hypothesis that selected ones would correspond to reality. We simulate systems plus the evolutionary process. Our utility functions, birth & mortality are filters to keep or remove agents of the system depending on its performance against its lifecycle.
We are applying a parallelism between DNA information and configuration or features in the agent. The features stablish the policy of the agent. For instance, the Gujarat project would differentiate between Hunter-Gatherer way of living from the Pastoralist way of living through this features.

Coevolution *When two or more species form an interdependent ecosystem the evolutionary progress of part of the ecosystem will generally induce co-evolutionary* *changes also in the other species* [44].

Long ago, bacteria and plancton dominated the seas. There was only microscopic life. Then appeared photonsynthesis based microbes. With Sun light and CO_2 chemistry they spread at a greater rate than their neighbours. Photosynthesis microbes filling the seas plus millennia produced the oxygen filled atmosphere of the planet. Changes in the atmosphere changed weather and many other chemical properties in the planet. The atmosphere contained ozone which barred the UV rays of the Sun which forbidded life in the surface. Then some individuals appeared with capabilities to get out of the water and breath the air of the surface. It is an example of mutual feedback between the environment and the evolving life beings. But this feedback can also happen between these beings, and then it is called coevolution[45]. When the adaptive process of an species produces a change that motivates selection of new adapting traits in other species which in turn affects the same way the first species we have coevolution. For instance, the relationship between a prey and a predator will induce coevolution. The hunting activities produce death in the prey species, hence motivating the selection of traits that give more probabilities in front of a predator attack. Predators feast on preys with feble traits. Old feble traits dissappear. Then predators must hunt the individuals without the feble traits. Incompetent predators will starve and a new elite will appear. A mutual selection pression is stablished between both species feeding changes of new “attacks” and “counterattacks” and “counterattacks” to the “counterattacks”.

Although we will not wire explicitly coevolution in the two studied social models we expect to see this phenomena. Sugarscape will be the framework for the competition between classical Sugarscape agents and sophisticated-AI ones. In Gujarat project we expect to observe coevolution between HunterGatherers and AgroPastoralist as they compete for resources and land. The adaptative strategies are considered as cultural traits. The ideas from Evolution will be adapted to study **Cultural Evolution**. We study the skills and strategies for resource explotaition. The succesful strategy, hunting and gathering versus agropastoralist activities or sophisticated AI versus classicla agent, will yield a greater probabilty of success to the agent. The evolutive-coevolutive framework will trigger a dynamic of selection and gradual change. In the long term we will observe the equilibrium properties reached by coevolution. For Sugarscape we think sophisticated agents will overcome classical ones, but for Gujarat our aim is to reach the coevolution results that lead to a equilibrium of the two adaptive strategies.


system
Ontological Reductionism
Pragmatical Re
model

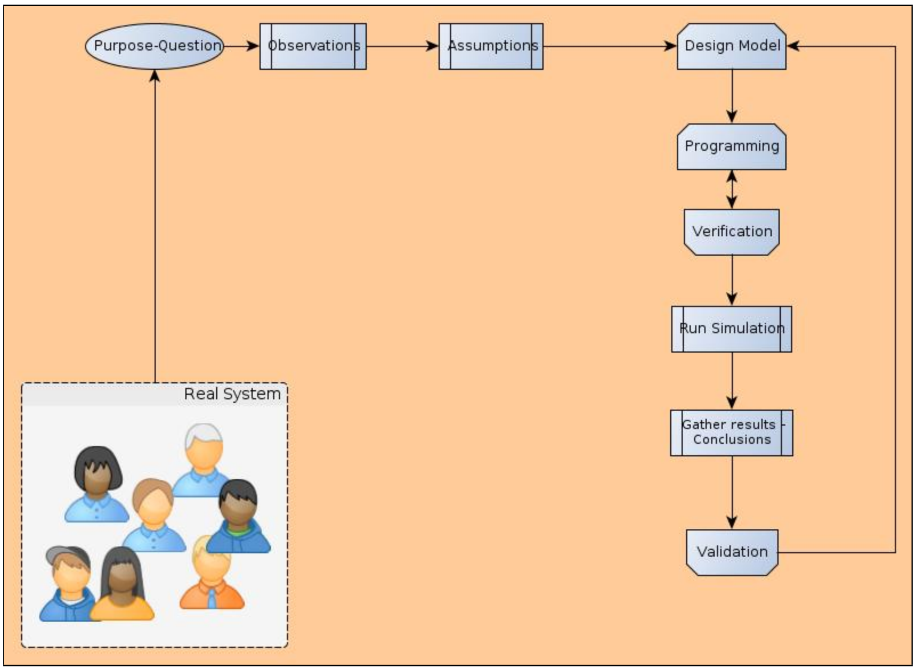


Figure 2.6: Stages defined in simulation-based research [7]

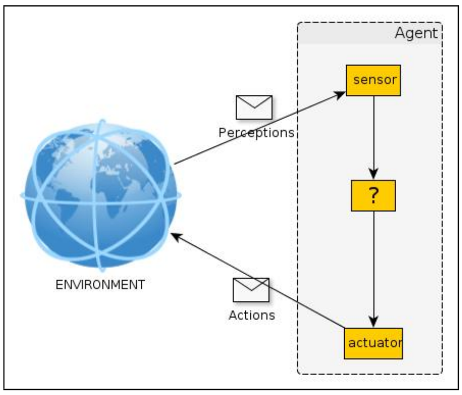


Figure 2.7: Agents interact with environment through sensors and actuators.

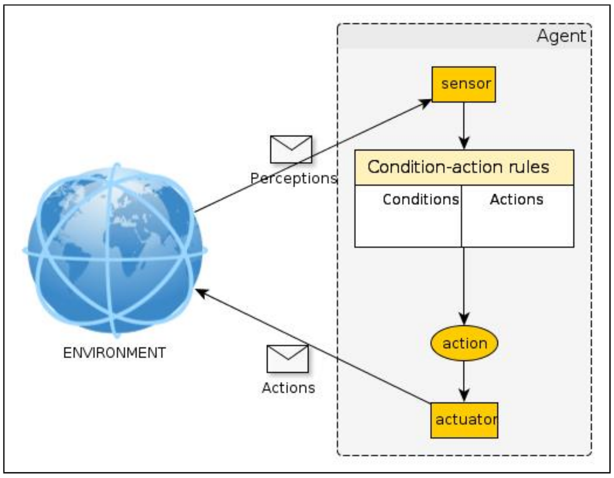


Figure 2.8: Simple Reflex Agent Architecture

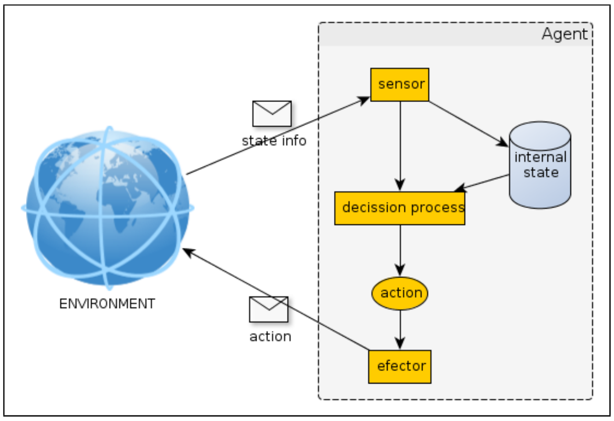


Figure 2.9: State Machine Reactive Agent Architecture

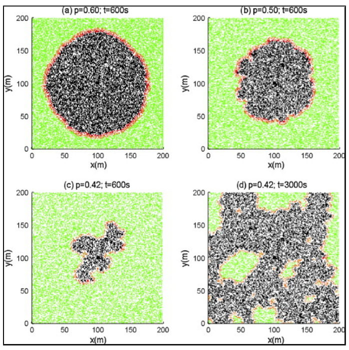


Figure 2.10: Percolation phenomena in fire spreading.

Figure 2.11: Development of spiral waves after hydrodynamic breaking of a concentric wave (Zhabotinsky and Zaikin, 1971).

Chapter 3

Platforms / Software packages

NetLogo...

rasters -¿ +- automata paralelism = 0 math libraries = 0? ML, AI,... ??? – efficiency why do you not use netlogo

Pandora/Cassandra

Pandora : C++, STL, Python API Parallelism

The software we will use to implement the model is the Pandora Library, created by the social simulation research group of the Barcelona Supercomputing Centre. This tool is designed to implement agent-based models and to execute them in high-performance computing environments (Rubio and Cela, 2010). It has been explicitly programmed to allow the execution of large-scale agent-based simulations, and it is capable of dealing with thousands of agents developing complex actions. The tool used has full GIS support to cope with simulations in which spatial coordinates are relevant, as in the case here, where we want to detect and compare spatial patterns. This library also allows the researcher to execute several simulations by modifying initial parameters, as well as to distribute particular executions with high computer costs by using a computer cluster. A cluster is formed by different linked computers (called nodes); the distribution divides the computing cost of the execution between different nodes, each of which executes a part of the entire simulation. As a result we will be able to run the simulation in a fraction of the time that would be needed if we were using a single computer. The results of each simulation are stored in hierarchical data format (HDF5), a popular format that can be loaded by most GIS. This feature is particularly useful, as we will also use GIS to analyse simulation results.

Finally, Pandora is complemented by Cassandra, a program developed to analyse the results generated by a simulation created with the library.

why do you use Pandora

Chapter 4

SugarScape vs Advanced Sugarscape

”Is it that simple? We just build agents that maximize expected utility, and we’re done?” It’s true that such agents would be intelligent, but it’s not simple. A utility-based agent has to model and keep track of its environment, tasks that have involved a great deal of research on perception, representation, reasoning, and learning. The results of this research fill many of the chapters of this book. Choosing the utility-maximizing course of action is also a difficult task, requiring ingenious algorithms that fill several more chapters, Even with these algorithms, perfect rationality is usually unachievable in practice because of computational complexity, as we noted in Chapter 1.

Why HG survived more than expected? (l’aplicacio de la pregunta 1) **interaction society vs envirm** 2 main forces that drive change. Environment as a drive for adaptation. Society : safety network, cooperation and competition
niche construction theory AP occupy space and cause HG displacement.

Uncertainty & Imprecision : state of resources(other foragers, climate stochacity),uncomplete know,... modelthinkingThe complexity wrought by the increases in information, adaptability, and interconnectedness implies a lack of predictability about what’s next.

Logic Programming, Semantic Networks : hard to represent the foraging expertise of H.G. -¿ reduce the problem to resource adquisition -¿ math modelling -¿ maximization -¿ planning.

.- reactive, proactive... .- adaptation .- reasoning .- planner

4.0.5 Planners, ...

UCT/MDP policies actions sectors

approaches : greedy, plan next action, ¿adding lookahead?

4.1 What is SugarScape?

4.2 Added advanced features

Same deduced trends and emerging dynamics

Realistic Adaptability to Parameter Perturbations

4.3 Solving critics against classic SugarScape

4.4 Experiments

Made assumptions about behavior of real systems
1st step, test if assumptions are reasonable
-Validation, or representativeness of assumptions
2nd step, test whether model implements assumptions
-Verification, or correctness

La seguent comprovacio fes-la en el modelatge o un altre capitol mes adient: Seed independence Ã¢â‚¬â€œ random number generator starting value should not affect final conclusion (maybe individual output, but not overall conclusion) Three key aspects to validate: -Assumptions -Input parameter values and distributions -Output values and conclusions

4.4.1 Initial Conditions

Montecarlo?

Emergence of stationary state; initial state := stationary state

4.4.2 Experiment features

Description

Hypothesis

Assumptions

Config

Results

Validation

Chapter 5

Gujarat Case Modelization

5.1 Introduction

Northern Gujarat is a marginal environment between the Thar Desert and the more fertile area of Saurashtra. This region is an ecotone, characterized by the seasonal influence of the monsoon where contrasting ecological niches are in tension and small climatic shifts can generate significant environmental changes, eventually affecting resource availability. Archaeological evidence points to the presence and possible coexistence in the area of groups of people with different resource management strategies and mobility behaviors: hunter-gatherers (HG); agropastoralists (AP); urban Harappans (UH). The aim of this study is to model resource management and decision making among hunter-gatherer groups in this region to explore adaptive trajectories and performance in relation to a) environmental variability and b) the appearance of other specialized groups . What factors play a role in HG persistence or disappearance in arid margins? Is the advent of agro-pastoral behaviour a big enough change to explain the disappearance of HG behaviour? What happens when there is an external influence, such as that by UH? Does climate change affect HG behaviour?

5.1.1 Hypotheses

In our starting hypothesis HG groups are adapted to marked seasonality (due to monsoon) in the arid margins of northern Gujarat. We intend to explore HG resilience considering: a) the appearance of AP, b) the appearance of an external attractor (UH) and c) climate change. We define resilience as the ability of the system to maintain its identity in the face of internal change and external perturbation (Carpenter 2001).

5.1.2 Aims and objectives

5.1.3 Knowledge Elicitation & Brainstorming

Interviews

ECOTONO (journal club)

ODD

5.2 Physical World / Environment

5.2.1 Statistical Modelling

Data Sources

Resource Pipeline

5.3 Antrophological Model

5.3.1 The Model

Knowledge Represent

Arithmetics, logics, probab models,... which & why

Decission Process

Hypothesis:richer agents

UPF hand to hand work:UCT algorithm

Methods

Ã‚Â¿state of the art?

Social Network

Ã‚Â¿state of the art?

Design

Organisational level design

Social structure

Interaction structure

Communicative structure

Normative structure

Coordination level design

Action model

Task model

Agent model

Plan model

5.4 Experiments

5.4.1 Initial Conditions

Montecarlo?

Emergence of stationary state; initial state := stationary state

5.4.2 Experiment features

Description

Hypothesis

Assumptions

Config

Results

Validation

Chapter 6

Conclusion

6.1 Achieved Objectives

6.2 Achieved Objectives

6.3 Comparison AI - Simple

6.4 Difficulties & Issues

6.5 Publications/CAA

6.6 Future Issues

Chapter 7

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