Computational Social Sciences

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Simulating Prehistoric and Ancient Worlds

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Chapter 1
Simulating the Past for Understanding the Present. A Critical Review

Juan A. Barceló and Florencia Del Castillo

1.1 Introduction to an Introduction

This book has been edited with the explicit idea of allowing the reader to imagine that virtual histories can be generated in a computer in the same way as in her/his mind. This is not a literary exercise, however, but an example of a radical revolution in the way of doing History as a social science. While computational models can be used to simulate real-world processes in great detail (e.g., some manufacturing processes), their greatest potential for historical explanation lies in using them as environments of systematic, controlled, virtual experiments in human social and socio-ecological dynamics (Bankes et al. 2002; Diamond and Robinson 2010; Barton et al. 2012; Barton 2013, 2014; Hmeljak and Goldstone 2016; Nakoinz and Knitter 2016; Cegielski and Rogers 2016). Importantly, such models are constructed from the bottom up, requiring the integration of knowledge about human social processes and theory about the relationships among individual actors and groups at multiple scales to create the algorithms which drive agent perception, decision-making, and action. Used in this way, building computational models can help refine our concepts about the operation of societies, and the models can serve as complex hypotheses that can be tested against the empirical record of archaeological, ethnological or historical research (Barton 2014).

The essays present in this book are the result of a special session organized during the annual conference of the European Social Simulation Association (ESSA) held at the Autonomous University of Barcelona (Spain) on September 2014. "Simulating the Past to Understand Human History"—SPUHH—for the first time in an ESSA con-

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ference gathered a multidisciplinary group of researchers interested in different developments of computer simulation in the archaeological and historical sciences. The most interesting part of this session was the increasing interest of a multidisciplinary community to implement computer simulations to solve historical problems. Not only archaeologists and historians are now interested on long term simulations, the presence of physicists, economists, computer scientists, historians, sociologists, geographers and anthropologists reflects the transdisciplinarity of this way of research. The papers selected to be published in this book express some of this excitement.

Most contributions are studies of the most remote past: prehistory and archaeology. But it does not mean that other historical periods cannot be made understandable recreating what people did and believed within a computer. In practice, then, the virtual pasts we can recreate within a computer are accessible in the sense that they tend to realign this paradigmatic new way of understanding the past with both the commonsense trivial idea that history is about what people did in the past (Düring 2014; Lake 2015; Lercari 2016; Cegielski and Rogers 2016; Marwick 2016).

1.1.1 A "New" Way of Understanding Human History?

History is a science that should look for causal affirmations about the formation processes of society. Therefore, the startpoint of historical research should be explaining past social events by showing how human behavior fit into a causal structure, that is to say, a vast network of interacting actions and entities, where a change in a property of an entity dialectically produces a change in a property of another entity (transformation).

This focus on the causal understanding of historical processes fits well with the notion that archaeology and history should offer something to contemporary society as an integrated science of long-term societal change and human-environment interaction (Rashevsky 1968; Abbott 1983; Turchin 2008, 2011; Hurley 2012; Gavin 2014; Lake 2015; Cegielski and Rogers 2016). History is not the identification of who did what in the past, but the quest for what produced a social action whose effects and consequences may be discerned in the present. Moreover, what generated those consequences was the interaction of a number of actions and entities, characterized by direct, invariant and change-relating generalizations. History as an explicitly scientific discipline should evolve from a subjective description of what we believe happened in the past, to an investigation of the causes of the present.

Descriptive chains of events, even if true, are not explanations but they are something to be explained. Clearly, nothing is gained if we introduce as an explanation of why some x occured, an indicator that some y occurred before or after (where x and y refer to different acts, events or processes). In some sense, causal interactions are the factors explaining why a social action was performed at a specific time and place, which is, its motivation or reason.

We can understand social action in the past only in terms of how humans did it. It is easy to see then that the concept of mechanism becomes the heart of this kind of causal explanation. Obviously, the word "mechanism" is here a parable of how social intentions, goals and behaviors are causally connected. A "social mechanism" should then explain how social activity worked, rather than why the traits contributing to these activities or workings are there (Bechtel and Richardson 1993; Machamer 2002; Craver 2001; Darden 2002; Glennan 2002; Gerring 2008; Ylikoski 2011; Maurer 2016). "Mechanisms are entities and activities organized such that they are productive of regular changes from start or set-up to finish or termination conditions" (Machamer et al. 2000, p. 3). No matter how long or complicated the causal process is, it can be called a mechanism if its description answers the question how did the cause bring about the effect.

We are adopting an analytical approach in which "social facts" are seen as generated, triggered, produced, brought about or "caused" by actions which themselves are in some sense "caused," or at least partly determined by the constraints presented by the social environments and situations in which such actions take place (Elster 1989). To explain a social event therefore means to describe the various causal chains linking all the elements involved (once those elements have been appropriately described and separated) in constituting a social fact.

These prospective for a new way of understanding human history are strongly related with current developments in Analytical Sociology. Such a term officially entered the sociological vocabulary with Hedström's *Dissecting the Social* (Hedström 2005) to denote the sociological perspective that seeks systematically to formulate and empirically test micro-founded, mechanism-based explanations of complex macro-level patterns and dynamics (see also: Bortolini 2007; Hedström and Bearman 2009a, b; Racko 2011; Raub et al. 2011; Bearman 2012; Edling 2012; Wan 2012; Opp 2013; Manzo 2010; 2014; Lombardo 2015). According to such definition, we can envisage a kind of "Analytical history" when trying to understand complex chains of change in terms of the discovery of patterns in transitions. To build such a discipline, and paraphrasing Manzo (2014), we should modify the actual way of describing the past and:

1. using concepts that are as clear and precise as possible to describe both the facts to be explained and the explanatory hypotheses/facts mobilized to explain them, while avoiding all linguistic obscurity and convolutedness (Pomeranz 2011),
2. mobilizing the best quantitative and qualitative empirical information available and use the technical tools best suited to describing the facts to be explained,
3. making emphasis on the social outcome(s) evidenced somewhere and somewhen to understand what happened and why. This can be done by first formulating a "generative model" that is, a model of a set of mechanisms, where a mechanism is a set of entities and activities likely to trigger a sequence of events (i.e., a process) likely to bring about the outcome(s),
4. providing a realistic description of the relevant micro-level entities and activities assumed to be at work, as well as the structural interdependencies in which these entities are embedded and their activities unfold,
5. translating our hypothesis of the social mechanism implied in the causal connections between events into a "generative model" in order to rigorously assess

the internal consistency of the hypothesis and to determine its high-level consequences,

6. comparing the predictions made by the generative model with the empirical description of the historical facts to be explained in order to assess the generative sufficiency of the mechanisms postulated,
7. injecting as much empirical data as possible into the generative model in order to prove that the hypothesized assumptions are not only generative sufficient but also empirically grounded, and reanalyze its behavior and high-level consequences.

A common objection to employing mathematical and formal models in the study of historical dynamics is that social systems are so complex that any mathematical model would be a hopeless oversimplification without any chance of telling us interesting things about these systems. As Turchin (2008, 2011) has argued, this argument is wrong: when any model appears to be "complex" then, the only way to analyze its behavior is through objective measuring and using mathematical language. "Naked" human brain is not a bad tool for extrapolating linear trends, but it fails abysmally when confronted with systems of multiple parts interconnected with nonlinear feedback loops. We need mathematical formalism to express our ideas unambiguously, and both analytical methods and fast computers to determine the implications of the assumptions we made (West 2011).

The advantage of formal modeling is that, by making explicit and unambiguous the relationships between events and also the intended scope, it is easier to determine whether the model is supposed to be applicable to some observed phenomenon and, if so, whether it adequately fits it (Lake 2015; Nakoinz and Knitter 2016).

1.1.2 The Past as a Virtual Model

The past is only accessible through the filter of a "model" built indirectly from personal narratives, written in the past and preserved in our present. It is then an artificial world, more or less imaginary, more or less reliable: a replica of what really happened. There is no doubt that historians have been creating virtual surrogates of the past since the early days of Herodotus and Thucydides. Such virtual worlds are expressed narratively, using verbal language. In them, the historian places herself in the context in which the action took place, but she is situated in a virtual world extracted from a narration—supposed to be true—by an individual having seen someone doing something in the past, or explaining her intentions when acting (Bouissac 2015; Lercari 2016).

In any case, virtual worlds that can be narrated using verbal language can also be expressed using computer languages (Mayfield 2007; Millington et al. 2012). In that sense, an Artificial Society can be seen as a set of autonomous software entities (the agents) having autonomy to "act", thus taking their own decisions based on computer instructions that "simulate" the goals of the humans they "imitate" and the state of the world in which they are supposed to be. Computationally speaking, virtual agents will consist of a body that contains a set of state variables and behavioral instructions.

As the real world constrains the structure and behavior of the real agents, the simulated historical context plays that role for the simulated agent system. The perceptions of the simulated agents need to have some origin in all factors external to that agent, and it has to be represented in a specific environmental model. Thus, complex agent models require rich contextual information that should be transferred to a virtual model of the "landscape". This global entity may carry some global state variables like its own dynamics. These dynamics also can be so complex, e.g., containing production of new entities, that one may assign some form of behavior with the simulated environment.

The successful completion of virtual agents' tasks should be subject to the decision and actions of others, and on the specific way the environment constrains or determines the performance of social action. These models as well as real phenomena, for example, the societies, are dynamic because they change in time; therefore, a model will consist not only of structure but also of behavior. To observe a model's behavior the passage of time on it is necessary and it is here where computer simulation functionality is required (Sansores 2007).

In this way, we can move the unit of analysis to the social system of situated agents, whose center of gravity lies in the functioning of the relationships between social activities, social action, operations, and social actors. The unit of analysis is thus not the individual, nor the context, but a relation between the two. Questions of scale are relevant to understand the advantages of computer simulation of historical events and processes. In a computer model of a remote past, the historian can disaggregate in reverse order to the way social organization has evolved: the highest level groups become independent systems, disassociated from other groups, and which can subsequently disaggregate into their respective subgroups. Because in a virtual past, agents, processes and environment interact with other components in multiple dynamic ways, in variable frequency and intensity across the nested hierarchical organization, the scale and direction of change at the system level is not necessarily proportional to the scale and direction of the phenomena that trigger it. Additionally, it is more the character of the interactions among components rather than their inherent characteristics that determines the behavior of a simulation at the system level.

This way of building "artificial societies" from individual building blocks representing the lowest units of analysis may be contrasted to macro simulation approaches that are typically based on generalized models where the characteristics of a population are averaged together and the model attempts to simulate changes in these averaged characteristics for the whole population. Thus, in macro simulations, the set of individuals is viewed as a single entity that can be characterized by a number of variables, whereas in micro simulations the structure is viewed as emergent from the interactions between low-level entities—the individuals.

In this framework, time is defined in terms of steps, and steps are defined by a transition system that has a recursive structure. History is then computable to the extent that it can be represented algorithmically as the successive states of some determined input → output function (Abbott 1983; Ponse 1996; Moschovakis 2001; Moschovakis and Paschalis 2008; Mahoney 2015). Such a computable system should consist of a set of states, a set of labels representing the agents and the actions, and a transition relation, prescribing for each state the possible 'next steps', i.e., what actions can be performed, and (per action) what state results. Selecting one state as the root (the initial state) then yields a formal representation of a process. In this framework, time is defined in terms of steps, and steps are defined by the computational process (Mayfield 2007). However, it is not useful to call "computation" just any non-trivial yet somewhat disciplined coupling between state variables. We also want this coupling to be intentionally set up for the purpose of predicting or manipulating, in other words, from knowing or doing something (Toffoli 2005).

This way of considering the particular—causal—relationship between successive steps in an evolving social system of agents, activities and products (both people, things or other actions) brings about the vocabulary of complex systems and chaos theory into the domain of social science and history. Complexity social science is not a radically new domain, but in the recent years, it has changed its emphasis dealing with the unpredictability and non-linearity of many real world social mechanisms (Ball 2003; Dendrinos and Sonis 2012; Guastello 2013; Schieve and Allen 2014; Youngman and Hadzikadic 2014; Wright-Maley 2015). Complex adaptive systems (CAS) represent systems which are dynamic in space, time, organization, and membership and which are characterized by information transmission and processing that allow them to adjust to changing external and internal conditions (Barton 2014). Complex systems approaches offer the potential for new insights into processes of social change, linkages between the actions of individual human agents and societal-level characteristics, interactions between societies and their environment, and allometric relationships between size and organizational complexity.

1.1.3 Testing the Virtual Model

This emphasis on computability and algorithms implies a correlated emphasis in formalization, on objectivity, but not necessary on "truth". Simulating the past is just a way of increasing the explanatory power of historical explanatory models and not necessarily their "truth likeness".

We never know for sure whether the generated computer model of historical transitions and changes actually describes what happened really in the past. It is important to take into account, however, that the mechanical generation of "hypotheses" is no end in itself. A simulation can be "suggestive", "imaginative", "relevant", "probable", "plausible", "credible" (Bankes et al. 2002; Garson 2009;

Reynolds et al. 2013; Whitley 2016; Balzer 2015; Stettiner 2016). A generative model of the past that we belive existed is just a formal device to generate explanatory arguments that can be fitted to reality or not. As such, an "historical model" is just a deductive system as valid as its initial axioms. The only we can check is the deductive coherence, that is, that explanatory arguments are expressions generated by the system and hence coherent with the embedded assumptions. The degree to which that potential is realized is a function of the empirical validity of substantive models and the degree to which these theoretical ideas have been implemented clearly and accurately (Cederman 2002; Lustick and Miodownik 2009; Peeters and Romeijn 2016; Marwick 2016).

If virtual explanatory models cannot be tested, they can be explored. When exploring the resulting computable model of a causal trajectory of "events", where each event is just a momentaneous state of the evolving system of agents, and all events within a trajectory constitute a "history", we can generate large numbers of virtual histories by perturbing the chain of events randomly or introducing randomized adjustments in initial conditions. Each one of these alternative "histories" can be used both to experiment with a theory of historical transition and social change (parameters are manipulated to test for predicted differences) and as a demonstration tool (parameters are manipulated to test for predicted robustness). When used experimentally, manipulations are allowed for agent-level parameters to test the global implications of behavioral assumptions, but also it is allowed to manipulate global parameters to test a macro theory about their implications at the micro scales.

Three methods of evaluating the validity of simulation models, over and above reliability, have been delineated by Taber and Timpone (1996):

- Outcome validity: demonstrating that outcomes in a simulation correspond to outcomes in the real world. Outcome validity corresponds to what can also be called "predictive validity" (Sterman 1984).
- Process validity: demonstrating that the process that leads to outcomes in a simulation corresponds to processes in the real world by calibrating initial parameters to empirically known historical data, in the sense proposed by Epstein (2006). Conversely, if the model omits real-world processes thought to be important in outcomes, the validity of model predictions is undermined even when those predictions have outcome validity. In some sense, it can also be considered a form of "predictive validity".
- Internal validity: demonstrating that simulation software validly represents the process being modeled. Put another way, has the model been fully debugged so that a researcher can be sure that only explicit model assumptions are modeled without unintended effects due to software artifacts? This is similar to what others have called "structural validity".

Turchin (2011) has advocated the use of historical experiments, meaning a planned comparison between predictions derived from two or more theories and data. In this way, we may focus on making predictions about the state of a certain variable for a certain past society, which is not known at the time when the predictions are made. For example, Model #1 says that the variable should be decreasing, while Model #2 says, no, it should be increasing. We then ask historians to look for ancient narratives, documents or archaeological data sets, and determine which of the theories is closer to the truth. As more such experiments are conducted, and if one of the theories consistently yields predictions that are in better agreement with empirical patterns than the other(s), our degree of belief into the better performing theory is consequently enhanced.

Precise historical case studies offer an opportunity to examine the internal logic posited by a theory of transitions between different events. A good case study will trace the causal processes observed in situ and determine whether they are consistent with a specific theory or challenge it. Historical case studies frequently focus on a specific spatial and temporal scale, varying from small settlements in the past, to regional land-use changes. They are particularly well suited for testing theories that predict that some event or process will never occur. Many different methods can be used to observe the case, including archaeological data, historical documents, ethnographical observations, remote sensing, surveys, censuses, interviews, etc. The various ways the system is measured may lead to some challenges when comparing cases with somewhat different observation procedures (Janssen and Ostrom 2006; Marwik 2016; Rubio-Campillo 2016; Heppenstall et al. 2016).

Therefore, empirical information, both qualitative and quantitative, can be used in a variety of ways. It can be used as input data to the computable model or as a means to falsify and test if not the model itself, its explanatory predictions. When historical data are used as an input, the focus might be to study a particular scenario, i.e., the proper historical circumstances from which the data is derived. By carefully calibrating start-up conditions to what is known from the past, crucial experiments can be designed to generate particular trajectories whose final states can be considered as "predictions", and then individually compared with what we know from the real past and measure its fitness. The more fitted are those latter states with equivalently dated historical data, the better the predictive power of the model. The revolutionary potential of this technique is associated with the fact that alternatively possible "futures" (or "histories") can be produced by varying initial conditions or a specific parameter setting of interest or by subjecting the theoretically specified model to random perturbations.

1.2 Recreating the Past in the Computer

1.2.1 From Animality to Humanity

Humans are animals. We have evolved from beings that were similar to modern apes, and those antecessors evolved from previous antecessors with features and behavior similar to modern squirrels, modern reptiles, modern amphibians, modern fishes, and modern bacteria. Animal behavior is a good example of social mechanism (without abstract beliefs nor complex motivations, nor desires and only simple instinctive intentions), and therefore it has been studied in formal terms since the times of Lotka (1910) and Volterra (1926). Those early works have been later implemented as computer simulations; see: Bryson et al. (2007), Petersen (2012), Bak (2013), Dow and Lea (2013), Lei et al. (2013), Boumans et al. (2014), Ma (2015), Topa et al. (2016) among many others.

There is a lot of "animality" within us, and if we want to know why we do what we are doing in the present, the only way is to understand our "degree of animality" and the historical process of differentiation from our "original" animality. This is not a defense of sociobiological approaches, but just the plain observation that we act as complex animals, and there is some kind of relationship—probably non-linear and non-monotonic—from animality to humanity. In any case, the most important aspect of investigation will not be the animal basis of human behavior, but the specific process of progressive differentiation in the way we take decisions —more or less rational—from the original animal instincts. There is no magic in this historical (prehistorical) process, but a series of explicitly mechanical biological processes that have historically constrained and determined human behavior: evolution and natural selection. Human evolution is a complex temporal trajectory of changes, transformations and modifications, some of which emerged slowly, and others very quickly. Complex phenomena in the present can be interpreted as the cumulative products of relatively simple processes acting over time. It is a domain where computational simulation tools and methods show their idoneity. Among recent essays in this direction, we can mention: Arenas (2012), Hoban et al. (2012), Kawecki et al. (2012), Ma et al. (2012), Kutsukake and Innan (2013), Messer (2013), Mode et al. (2013), Villmoare (2013), Schlötterer et al. (2014), Smaldino et al. (2013), Acevedo-Rocha et al. (2014), Hunemann (2014), Lehman and Stanley (2014), Vevgari and Fioley (2014), Roseman et al. (2015), Peart (2015), Shamrani et al. (2015), Smith et al. (2015), Hatala et al. (2016), Lieberman (2016), Polly et al. (2016). An interesting related approach is that of considering the analogy of robot evolution to understand what may be going on human evolution (Wischman et al. 2012; Bongard 2013; Mitri et al. 2013; Eiben 2014; Muscolo et al. 2014).

In any case, natural selection and evolutionary mechanisms have affected animals and humans not only in morphology but in the development of pre-human behavior (Premo 2005; Barton and Riel-Salvatore 2012; Pradhan et al. 2012; Witt and Schwesinger 2013; Kramer and Otárola-Castillo 2015; Tang and Ye 2016). It is also the question of the origins of "intelligence" and complex decision making (Gabora and Russon 2011; Gabora and DiPaola 2012; Kurzweil and Ray 2012; Chandrasekaran 2013; Pringle 2013; Guddemi 2014; Ross and Richerson 2014; Geary 2015; Cowley 2016) and also culture. This is not the place to define what is culture, but recent work suggests its computable basis (Belew 1990; Goodhall 2002; Richardson 2003; Bentley et al. 2004; Henrich 2004; Harton and Bullock 2007; Enquist et al. 2011; Gabora and Saberi 2011; Premo 2012, 2015; Premo and Kuhn 2010; Gabora et al. 2013; Messoudi 2011; Crema et al. 2014a, b; Acerbi et al. 2014; Cowley 2016; Gong and Shuai 2016).

An interesting example of how computer simulation may be used to test hypothesis about human evolutionary history is Agustí and Rubio-Campillo (2016). These authors deal with Neanderthals fast extinction between 40,000 and 30,000 years ago. The authors suggest a much simpler scenario, in which the cannibalistic behaviour of Neanderthals may have played a major role in their eventual extinction. They show that this trait was selected as a common behaviour at moments of environmental or population stress. However, as soon as Neanderthals had to compete with another species that consumed the same resources cannibalism had a negative impact, leading, in the end, to their extinction. To test this hypothesis, Agustí and Rubio-Campillo have used an agent-based model computer simulation. The model is simple, with only traits, behaviours and landscape features defined and with no attempt to re-create the exact landscape in which Neanderthals lived or their cultural characteristics. The basic agent is a group of individuals that form a community. The most important state variable in the model is the location of the group, coupled with a defined home range and two additional factors: cannibalism and the chance of fission. The result of the simulation shows that cannibalistic behaviour is always selected when resources are scarce and clustered. However, when a non-cannibalistic species is introduced into the same environment, the cannibalistic species retreats and the new species grows until it has reached the carrying capacity of the system. The cannibalistic populations that still survive are displaced from the richest areas, and live on the borders with arid zones, a situation which is remarkably similar to what we know about the end of the Neanderthals.

In this book, Ingo Timm et al. (Chap. 2) explore the possibility of simulating some aspects of hominine prehistoric behavior, notably dispersal and migration. This subject has also been approached by Mithen and Reed (2002), Beyin (2011), Eriksson et al. (2012), Wren (2014), Wren et al. (2014), Thompson et al. (2015), Hölzchen et al. (2015), Kealy et al. (2015), Romanowska et al. (2016), Vahia et al. (2016). Timm et al. suggest a series of reflections for a future simulation, and not a current implementation. It is very instructive the way they approach the implied mechanism. Among other things, authors suggest that ecological variations and demographic pressure likely influenced the dispersal of hominins. The increasing number of members may have required band ("tribes"?) to split up into smaller groups in order to keep group sizes manageable. Furthermore, changes in climatic, geographical or sea-level conditions may have been responsible for hominins to move towards Eurasia, too. But also changes of physical abilities increasing the hominin's stamina as well as the absence or occurrence of diseases outside their former habitat may have caused migration.

Timm and co-authors have programmed their virtual human antecessors with a concrete reason to leave their original habitat, and detailed consideration of potential influencing factors. Although "animals" in the biological sense, these virtual hominins are seen as utility-based agents, considering changes in their environment and evaluating the consequences of their actions in advance. Furthermore, the "happiness" regarding new states created by performing an action is considered as well. Transferred to the challenges hominins faced when crossing

Africa towards Eurasia, this happiness can be equated with the sufficient availability of food and other resources of vital importance. However, hominins are not the only actors which are part of the Out-of-Africa-Hypothesis that deliberate their behavior in regard to their actions. The behavior of carnivores might for example be modeled by using a similar approach as well. Choosing appropriate prey as well as selecting, defending and marking their territory are processes which can be modeled using intelligent software agents. But not all aspects of the Out-of-Africa-Hypothesis can and should be modeled as decision-making mechanisms. There are also other factors affecting the dispersal processes such as outside influences (weather or climatic changes) or the condition of the landscape (vegetation or geological formation). These factors are modeled by Timm et al. as part of the environment the agents are located in. All of these factors influence the land's potential for hominin dispersal. Yet, the potential is not a constant value but it may change over time.

It can be of interest to compare the dispersal mechanism of pre-humans, to the motivations and intentionality of movement and dispersal by modern humans of "prehistoric" times, with motivations different from modern humans of present times, and even our antecessors from a more recent past with motivations assumed to be like ours (Young 2002). Janssen and Hill (Chap. 3), Oestmo et al. (Chap. 4), Fort et al. (Chap. 5) and O'Brien and Bergh (Chap. 6) deal with this issue in different historical contexts. Jansen and Hill begin their analysis with the assumption that among early humans it may have existed a relationship between group size and movement and whether resources are dispersed or clumped in space, because this relationship exists and it is well attested in animal behavior. The general prediction is that movement should be less frequent in patchy environments because foragers should stay within a patch until foraging gain rates drop below some critical value before moving on. The authors explore different resource distributions and how they affect optimal group size, movement frequency and average daily return rate per hunter. They also examine the effect of targeted camp movement (vs. random) on the return rate that can be obtained in more patchy environment.

Janssen and Hill (Chap. 3) consider the ecological parameters of the environment and prey characteristics measured in the Mbaracayu Reserve, Paraguay. They have actually measured the ethnographically known Ache hunter-gatherers moving in the real world while searching for prey and other resources in any of the seven vegetation types' landscapes. Therefore, the probability of encountering a prey or a resource of a specific type can be estimated, a value that it is unknown for hominins, and it depends on very general assumptions. Virtual hunter and gatherers in Janssen and Hill model have no explicit beliefs or desires, but a very general intention to survive by hunting and gathering. They are also implied in more social activities, like cooperative pursuits that impose on hunters the need to move though the landscape in a semi coordinated fashion. Instead of assuming that any human decision should be rational, and social processes are the consequence of plain and linear mechanisms, Janssen and Hill investigate the most probable way the agents residing in a camp together determine whether the average weight of meat hunted over the last few days is above a certain threshold. If so, people decide not to move and the camp remains in its location for another day, if not, agents migrate and the campsite is moved to a new. These two decision criteria define four broad strategies for a camp: whether it is adaptive or not, and whether new locations are targeted or not.

Oestmo et al. (Chap. 4) analyze how the actual placement of resources affects hunter-gatherer movements. The authors compare random walk behavior of virtual hunter-gatherers from prehistoric times with two other walk behaviors. The first one is called “seeking walk”. During seeking walk simulations, the forager will move towards the nearest material source if the level of the materials in the toolkit is lower than a certain number. This means that at any moment when a foragers’ toolkit is empty it will seek to acquire new material. The second alternative walk model is termed the “wiggle walk” where it is assumed that a forager has a direction and moves forward one cell each time step. At each time step, the forager changes the direction by taking a left turn with a degree drawn from a uniform distribution between 0° and 90°. Both the seeking walk, which is a simplified analogy for a forager that returns to a stone cache, and the random walk behavior show that increased clustering of the raw material sources leads to increased time without raw materials in the tool kit. However, time between procurement instances and time without materials in the tool kit have different implications. If a forager can stockpile a cache at a central location and can return to such a place then the forager can go extended periods without procuring because it could return to the cache to fill up on raw materials. On the other hand, these results suggest that if random walk takes the forager away from the central location and never or very seldom returns directly to a stone.

O’Brien and Bergh (Chap. 6) go forward in the investigation of the rationality of people moving. Instead of considering dispersal in a macro scale, they opt for investigating local movement in particular well known geographical areas. Strong rationality is here equated with analytically calculated Least Cost Path, as the values assigned to these models are derived from legitimate factors which influence movement, such as distaste for steep slopes, the relative difficulties of traversing different soil types, and absolute obstacles. However, these authors go well beyond the logic of “animal” movement, and they consider that social factors should not be ignored for understanding human movement, and taboos, traditions, exclusivity can be incorporated into such models. In their case study, the aim of navigating to a known settlement presupposes a minimum pre-existing cognitive map, which may be constructed from personal experience, third-party knowledge and topographical gossip. They also consider the need to include the role of a leader, and some followers. Nevertheless, they do not consider the mechanisms underlying the emergence of such differentiation. In this way, the computer simulates how route ways are established through a series of discrete actions around those natural features, acted out by individual agents over time. Modelling allows the investigation of the overall evolution of a route way as individual agents have access only to local information, allowing them to approach the optimal path over time through a process of iterative attempts to traverse a landscape. The environment of North Offaly in the Irish Midlands is used as the study area, as it is a landscape of natural route ways and obstacles for which we have rich archaeological and documentary evidence supporting interpretation of movement.

Fort et al. (Chap. 5) consider a different way to analyze human motivated movement. These authors emphasize long run movements of people at a spatial macro scale as a consequence of population increase. They consider the case study of Neolithic times, when farmers go away from their birth place when available land saturates. At a global scale the set of individual migrations can be compared with a single wave or front, advancing to neighboring areas. In this contribution, the mechanism is entirely adaptive, and no rationality, except for the intention derived from recognizing the "need" of suitable land for farming once there are no empty places in the immediate vicinity due to population increase. At this macro scale, the rationality of individual decisions can be studied in terms of the central tendency of the accumulation of individual decisions. In that way, the dispersal behavior of the population can be probabilistically based on the mean age difference between parents and their children, and a set of dispersal distances per generation and their respective probabilities.

Fort et al. contribution vindicates the mechanical nature of some apparently intrinsically human decisions: migration. At first sight, it would not be an example of the evolution of human intelligence, but a kind of animal behavior, that is, instinctive. However, in homogeneous environments it is reasonable to expect that, on average, intelligent beings will not prefer any specific direction. Obviously, this is not the single possibility. As the comparison between the different contributions on human movement in pre-industrial societies show, the intrinsic human definition lies in the historical variability of such decisions. Other authors have addressed the same subject from different perspectives (Hazelwood and Steele 2004; Goldstone and Roberts 2006; Fitzpatrick and Callaghan 2008; Bevan 2011; Callegari et al. 2013; Reynolds et al. 2013; Silva and Steele 2015; Wren 2014; Lanen et al. 2015; Sanders 2015). It is interesting to compare Fort's results with Wren's (2014) hypothesis combining a model of cognitive dispersal with the wave of advance mechanism. Wren's experiments quantify the impact of cognition on dispersal velocity and wave pattern. The results show that the greater the level of cognitive complexity, the slower the wave of advance. Increased heterogeneity of the environment further decreases wave velocity when cognition is involved in mobility. Random movement, i.e., non-cognitive mobility, provides the highest velocity across almost all landscapes. This suggests that previous research may have either overestimated the importance of cognition in facilitating dispersal events, or has underestimated the rate of population growth and per generation dispersal distance of populations. If this is a distinctive feature of pre-human populations or even Paleolithic hunter-gatherers is something that should be analyzed further, by exploring the close relationship between cognitive complexity, the spatial heterogeneity of the landscape, and dispersal potential and velocity.

In this way we can approach the behavioral, cognitive and social consequences of evolutionary processes over the human lineages (see more discussion about those issues in Janssen et al. 2005; Griffith et al. 2010; Kempe et al. 2014; and Ackland et al. 2014; Kovacevic et al. 2015; Romanowska et al. 2016). Through the comparison of the mechanics of dispersal movements in animals, pre-humans, and humans we can arrive to understand the real impact of "intelligence" on mobility and survival in terms of an evolutionary trajectory of historically contextualized motivations and intentions.

1.2.2 Hunting-and-Gathering in the Past Explains How We Have Survived Until the Present

Previous discussion on simulating movement and dispersal among pre-humans and humans at different periods of history reveal the strong naturalistic character of many human decisions, and the constraints imposed by environment. Many modern historical simulations concentrate on that aspect of human behavior in the past.

Prehistoric hunter-gatherers have been studied many times from the point of view of animal foraging behavior, stating that human agents also forage in such a way as to maximize their net energy intake per unit time. In other words, it is assumed they should find, capture and consume food containing the most calories while expending the least amount of time possible in doing so. This is the old Malthusian view on population increasing exponentially while food production would have increased only linearly, in constant increments (Portugali 1999; Read and LeBlanc 2003; Lane 2010; Cai 2012; Schlueter et al. 2012; Levin et al. 2013; Hritonenko and Yatsenko 2013; Ribeiro 2015). Consequently, population growth would have generated on the long term the depletion of "natural capital", and declining biodiversity. Since these trends undermine the probabilities for survival, when "human load" exceeds local carrying capacity it erodes environmental potential. These concerns were the first to attract the interest of archaeologists who found the possibility of the computer modelling of hunter and gatherer survival (Zubrow 1971; Thomas 1972; Wobst 1974; Joachim 1976). The understanding of many ecological concepts such as adaptation, energy flow and competition hinges on the ability to comprehend what food items such human agents selected, and why. Nevertheless, it is obvious that if humans were in the past just like any other animal forager or predator, we would say that prehistoric hunter-gatherers survival would have depended just on the availability of edible resources. Given what we know about the natural irregularity of natural resources yield, *Homo sapiens* would have extinguished many times since their African origins!

The hypothetical explanation of "adaptive" mechanisms in human prehistory should be much deeper than that. For instance, in the case of gathering, we can assume that posterior probabilities for gathering success, and hence of survival, may be completely defined by the probability of plants availability. In case the environment is full of available resources ("rich world hypothesis"), the probability of finding enough plants to eat and make instruments is very high, and prior probabilities for survival are also high; in the case of low availability, prior probabilities for survival would be lower. Hunting seems to be a much more complex activity, whose success and hence the posterior probabilities of survival are less deterministically affected by the availability of animals in the area. If a social agent cooperates with another agent, the chances of hunting success are higher, even in the case of low animal availability, and so on. Availability of technology can also increase posterior probabilities of survival even in the case of low prior priors due to scarcity. Therefore, a successful explanation of hunting and gathering survival in prehistory needs additional factors and dependencies to be able to calculate posterior probabilities of survival (Del Castillo and Barceló 2013; Barceló et al. 2015).

The single most obvious constraint of human action in a particular environment is population size, especially when the means of production seem to be underdeveloped (hunting-and-gathering). Many modern computer simulations on human demography are centered on modeling the particular dependence on annual fertility tables and adopt a fecundity based model. The odds of conception for any one mating event can be kept constant for a female agent of a given age, and the probability of reproduction therefore becomes dependent on the frequency and timing of the female agent's mating activity. This allows for realistic fertility variations as a function of mating behavior frequency (and thus contextual opportunity in the form of access to male sexual resources) and the variations of individual agent fecundity over time. An important source of artificial structure (imposed annual fertility rates) is thus removed from the model, allowing the simulation's results to emerge more freely, especially in the very long term. Long term variations in access to reproductive partners can now have their full effect on fertility rates. This also opens the door to a much closer modeling of environmental and social factors affecting fecundity on an individual agent level (Stajich and Hahn 2005; Fletcher et al. 2011; Billari and Prskawetz 2012; Brandenburg et al. 2012; Eriksson and Manica 2012; Rogers and Kohler 2012; Santow 2012; Koenig et al. 2013; Dyke and MacCluer 2014; Dyble et al. 2015; Guillot et al. 2015; Kaur and Kaur 2015; Pastor et al. 2015; Bentley et al. 2016; Moya et al. 2016; Bauch and McElreath 2016; Chan et al. 2016; Rodríguez et al. 2016).

How simple and well adapted to the local carrying capacity is population growth in a hunting gathering economic system? Whereas the demands of non-human species on their habitats are fixed and limited, human demands, even during the most remote period of our past, have been hardly simple and are constantly evolving. Chapman (1980), Samuels (1982), Read (1998), Costopoulos (2002) have created social reproduction models based on modern ethnography of hunters and foragers groups, taking into account the social and political aspects of marriage and complex way of reproductive tasks scheduling influenced by political and ideological goals.

Smaldino et al. (2013) investigate the evolution of a population under conditions of different environmental harshness and in which selection can occur at the level of the group as well as the level of the individual. The authors focus on the evolution of a socially learned characteristic related to individuals' willingness to contribute to raising the offspring of others within their family group. They find that environmental harshness increases the frequency of individuals who make such contributions. However, under the conditions the simulation stipulates, the authors also find that environmental variability can allow groups to survive with lower frequencies of helpers.

White (2013, 2014, 2016) has built an Agent Based Model representing a hunter–gatherer system taking into account parameters such as mortality, fertility, and mean age. The demographic characteristics of a living population are the result of numerous human-level interactions and behaviors: persons and households make decisions about marriage and reproduction based on their individual circumstances within the context of "global" conditions that exert effects and constraints on all members of the population (e.g., the physiological factors that govern the length of the female reproductive span, ecological circumstances that affect the contributions of children to subsistence, cultural rules affecting marriage behaviors, etc.). The demographic characteristics of these systems (e.g., population age structure, mean fertility, mean mortality) emerge through a large number of human level interactions and behaviors related to marriage, reproduction, and mortality. The model has three main "levels": person, household, and system. Each agent in the model represents an individual person who is a discrete entity with a unique identity. Households are co-residential groupings of persons that form through marriage and change in size and composition primarily through marriage, reproduction, and mortality. Social links define relationships between pairs of living persons and are used to enforce marriage prohibitions. The system of the model is composed of all persons and households in existence at a given point in time. Methods representing marriage, reproduction, and death operate at the person and household levels in this model. Individual persons and households make probabilistic decisions about reproduction, marriage, and infanticide based on the current dependency ratio of the household (the ratio of the number of consumers to the number of producers in the household). Although the base probabilities affecting reproduction and mortality are set by model-level parameters (i.e., they are the same across the population), the economic circumstances of individual households affect the behavior of individuals in those households on a case-by-case, step-by-step basis. The households that form within the model systems are verifiably consistent with those documented among ethnographic hunter–gatherers in terms of their size, composition, and developmental cycles. Results of the computational implementation of the model suggest that changes in family-level economics can be coincident with subsistence intensification contributing to the emergence of social complexity among prehistoric hunter–gatherers by creating the conditions for a "rich get richer" scenario. Lowering the age at which children make a significant contribution to subsistence (e.g., through the broadening of the diet to include mass-harvested and "low quality" foods). This practice could have relaxed constraints on family size polygynous families economically viable. Positive feedbacks between the productive and reproductive potentials of larger families produce right-tailed distributions of family size and "wealth" when the productive age of children is low and polygyny is incentivized, permitting the emergence of hereditary social distinctions.

Crema (2014) assumes that human groups are characterized by a non-linear relationship between size and per-capita fitness. Increasing group size has beneficial effects, but once a certain threshold is exceeded, negative frequency dependence will start to predominate leading to a decline in the per-capita fitness. Such a relationship can potentially have long-term implications in the spatial structure of human settlements if individuals have the possibility to modify their fitness through group fission-fusion dynamics. He illustrates the equilibrium properties of these dynamics by means of an abstract agent-based simulation and discusses its implication for understanding long-term changes in human settlement pattern. Results suggest that changes in settlement pattern can originate from internal dynamics alone if the system is highly integrated and interconnected.

The second part of the problem when trying to couple the social and the environmental lies in modeling carrying capacity and the capability of prehistoric humans, even with inefficient technology to alter and modify it. Demographic and expansion behaviours of groups are largely influenced by the distribution and availability of resources. This has been an important domain for research on computer modeling and much effort is still being invested (Keane et al. 2002; Sept 2007; Seth 2007; Wainwright 2008; Garfinkel et al. 2010; Janssen 2010; Dearing et al. 2012; Van der Bergh et al. 2013; Ch'ng et al. 2013; Marean et al. 2015; Millington et al. 2013; Burch et al. 2014; Jones and Richter 2014; Balbo et al. 2014; Barton et al. 2014; Feola 2014; Bentley and O'Brien 2015; Codding and Bird 2015; Rammer and Seidl 2015; Rodriguez et al. 2015; Wood et al. 2015; Iwamura et al. 2016; Boumans et al. 2015; Polhill et al. 2016; Sarjoughian et al. 2016). The problem is that human–nature systems have been traditionally studied separately, either as human systems constrained by or with input from/output to natural systems (usually including the physical environment and the corresponding ecosystem), or as natural systems subject to human disturbance. This chasm between natural and social sciences, along with such unidirectional connections between natural and human systems, has hindered better understanding of complexity (e.g., feedback, nonlinearity and thresholds, heterogeneity, time lags). In the process of truly coupling human activity and natural environment, computer simulation approaches allow understanding how human decisions and subsequent actions would change (at least affect) the structure and function of many natural systems. Such structural and functional changes would in turn exert influence on human decisions and actions (An 2012; Widlock et al. 2012; Sarjoughian et al. 2015). In this sense, Dorward (2014) proposes a 'livelisystems' framework of multi-scale, dynamic change across social and biological systems. This describes how material, informational and relational assets, asset services and asset pathways interact in systems with embedded and emergent properties undergoing a variety of structural transformations. Related characteristics of 'higher' (notably human) "livelisystems" and change processes are identified as the greater relative importance of (a) informational, relational and extrinsic (as opposed to material and intrinsic) assets, (b) teleological (as opposed to natural) selection, and (c) innovational (as opposed to mutational) change. This suggestion provides valuable insights into the real understanding of 99 % of human history, when survival was only possible through hunting and gathering.

We may wonder about the unbalanced application of simulation, where the biological side (as in human evolution) has greatly benefitted from simulation while the more "sociological" aspect of archaeological simulation remains a challenge (Lake 2014; Cegielski and Rogers 2016). To understand the coupling between human and environmental systems in prehistory, researchers should study human collective behavior as a consequence of the indirect influence individual agents and organized populations of agents may have had on other hunter gatherers given that each one responds to an environment altered by the behavior of other agents. The general purpose of this way of studying prehistory seems to be the simulation of potential historical situations in which agents periodically may have modified their output behavior when they were able to learn to predict how the action at a previous step modifies the input at the next step. Many individuals can end up near each other simply because they tend to approach the same localized resource such as food or a water source. In these circumstances too, the agents' behavior resulting in social aggregation has not evolved for that function. Each individual approaches food or water for eating or drinking, not for social purposes. However, even if it is a simple by-product of learning nonsocial behaviors, social aggregation can be a favorable pre-condition for the emergence of social behaviors such as communication and economic exchange among individuals that happen to find themselves near each other. In other circumstances, however, social aggregation may not be simply a by-product of behavior emerged for other purposes but is the result of behavior which has emerged exactly because it produces spatial aggregation (Lake 2000; Costopoulos 2001; Berman et al. 2004; Goldstone and Ashpole 2004; Goldstone et al. 2005a, b; Parisi and Nolfi 2005; Janssen and Ostrom 2006; Kalff et al. 2010; Barton et al. 2011; An 2012; Rounsevell et al. 2012; Ch'ng and Gaffney 2013; Boone and Galvin 2014; Messoudi 2014; Clark and Crabtree 2015).

Related to this debate, in the present book, Saqalli and Baum (Chap. 8) consider that humans have historically formed complex groups and societies that are bound to their environment in more or less intense interactions, the imprint of which are found in landscapes. A society and its evolution can be studied as driven by their calorie and resource demand and constrained by environmental parameters. Thus, archaeological/paleo-environmental models can either directly analyze the social interactions between agents, or use the landscape as a reference plane. In any case, it is the mutual interdependence of humans and their environment that is in the focus: environment and natural resources are quickly and directly affected by human activities and at the same time, humans are directly and rapidly affected by the availability of natural resources.

However, it is important to take into account that not any measured differences in survival between individuals through time reflect necessary differences in fitness Brookfield (2001). Fitness represents an expected outcome, and what actually happens in small populations differs from expectation because each generation represents a sample, with an attendant sampling error, of the individuals produced by the previous generation. The fitness of a population is related only probabilistically to real events; sudden advantageous changes and transformations are usually lost by chance.

Janssen and Hill (Chap. 3), and Oestmo et al. (Chap. 4) have modelled the particular way in which human prehistoric behavior can be considered as "adapted" to environmental conditions (see also Read 2008; Kline and Boyd 2010; Collard et al. 2011; Kuhn 2012; Wood et al. 2015; Caiado et al. 2016; Martin and Fahrig 2016). In the first case, Janssen and Hill examine how optimal group sizes and movement frequency are affected by more dispersed or more clumped resource distributions, when the absolute number of resources in the environment is held constant. They also examine the effect of targeted camp movement (vs. random) on the return rate that can be obtained in more patchy environment. The model uses real measured parameters from a modern foraging society to create an agent-based model, which subsequently allows simulating a more or less patchy environment in order to determine how those changes affect optimal group size and mobility. They conclude that human foragers, by knowing the landscape and the spatial location of better habitats, and moving to facilitate hunting in those areas, can gain a substantial advantage from that knowledge. In the other contribution, Oestmo et al., investigate whether changes in stone tool raw material frequencies in an archaeological assemblage could be considered a reliable proxy for human forager adaptive variability. Two different patterns are obtained in their simulated model. First, when a forager engages in random or wiggle walk, a more clustered environment leads to lower average raw material richness in the toolkit. As clustering increases, the forager will on average move longer periods without encountering a source. Due to this and the fact that the forager use a material at every step, the forager will then when encountering a source fill up the tool kit to the maximum capacity resulting in one raw material dominating the make-up of the tool kit in terms of frequency. In the other pattern, the forager engages in a seeking walk and seeks the closest raw material sources when the tool kit is empty. In this case, the increased clustering of raw material sources leads to increased raw material richness. The richness increases because when the forager seeks the nearest raw material source, and this nearest raw material source is clustered with other sources, it increases the chance of encountering other sources in close proximity that in turn could lead to increased richness.

1.2.3 Rationality Within the Computer. The Myth of the Stupid Prehistoric Savages

Socio-ecological models make emphasis on physiological motivation, such as hunger, thirst, fatigue and comfort. In this case agents generate their goals around some physiological trigger, e.g., getting hungry. If needed, other types of motivation can be employed, such as safety. This is the case in some of the simulations presented in this book (notably Virtual Hominines in Chap. 2, and Virtual Hunter Gatherers in Chaps. 3 and 4) whose intelligence is expressed in the way they look for the satisfaction of their full stomachs. However, if physiological motivation is the only source of directness in the computer simulation of human behavior we may end with undesired, uniform behavior. Trescak et al. (Chap. 14) propose to configure motivational modifiers, which affect the decay rate of a given motivation. For example, a hunger modifier affects the pace in which an agent gets hungry. If such modifiers are different for every agent—then every individual follows its own circadian rhythm, executing goals at various time intervals, increasing believability of the simulated population.

In a sense, even computational agents implemented as biped stomachs can be considered "rational agents" because they make optimal decisions: they "want" to survive, and then they need to look for accessible resources. They have been programmed with the instinctive knowledge that they should hunt animals and gather for vegetables to acquire food, and therefore they hunt, gather and move looking for preys and resources. Janssen and Hill (Chap. 3, see also Janssen and Hill 2014) assume human hunting behavior is consistent with Optimal Foraging Theory, which is a model of animal behavior. In this way, hunter-gatherer foraging strategies—optimal group size, movement frequency and average daily return rate per hunter—are examined as the consequence of environmental factors—differences in resource distributions—and not because of social or political dispositions. Rationality here is approached in the sense of biological survival and not in terms of social reproduction. According to that, there is no difference in the programmed mind of hominid antecessors and Homo sapiens sapiens!

Human (and even animal) rationality is much more complex than expected and therefore, it is easy to conclude that deterministic relationships between environmental stress and social change are inadequate (Mithen 1991; Costanza et al. 2007; Gardner 2012; Polechová and Barton 2015; Bryson 2015). The challenge of a computer simulation of human behavior is them to assess the impact of culture and knowledge on decision making behavior (An 2012).

We need to implement a form of intelligence beyond literal rationality if we want our historical models be credible. Socially intelligent agents (SIAs) should be defined as agents that do not only from an observer point of view behave socially but that are able to recognize and identify other agents and establish and maintain relationships to other agents (Dautenhahn 1998). The process of building SIAs will always been influenced by what the human as the designer considers "social," and conversely, agent tools that are behaving socially can influence human conceptions of sociality. A cognitive technology (CT) approach toward designing SIAs would afford an opportunity to study the process of (1) how social agents can constrain their cognitive and social potential, and (2) how social agent technology and human (social) cognition can co-evolve and co-adapt and result in new forms of sociality. Aspects of human social psychology, e.g., storytelling, empathy, embodiment, and historical and ecological grounding, can contribute to a believable and cognitively well-balanced design of SIA technology in order to further the relationship between humans and agent tools.

One of the very first computer simulations of prehistoric hunter gatherers was that of Robert Reynolds (1986). He explicitly approached the problem of rationality in hunter-gatherer decision-making in terms of:

- the ability of each member to collect and process information about the resource distribution,
- the extent to which information is shared among members,
- the specific sets of decision available to each member, and
- the way in which the individual decisions are integrated to produce a group decision.

On that basis, Reynolds defined a general approach to programing that can also be considered as a general program for rationality in social evolution studies. He calls Cultural algorithm (CA) a specific kind of evolutionary computation framework where there is a knowledge component that is called the belief space in addition to the population component. The belief space of a cultural algorithm is divided into distinct categories representing different domains of knowledge that the population has of the search space. The belief space is updated after each iteration by the best individuals of the population. The best individuals can be selected using a fitness function that assesses the performance of each individual in population much like in genetic algorithms.

Reynolds lists different belief space categories:

- Normative knowledge: A collection of desirable value ranges for the individuals in the population component—e.g., acceptable behavior for the agents in population.
- Situational knowledge: Specific examples of important events—e.g., successful/unsuccessful solutions
- Temporal knowledge History of the search space—e.g., the temporal patterns of the search process
- Spatial knowledge Information about the topography of the search space

The "best-fitted" individuals of the population can update the belief space via an update function. Also, the knowledge categories of the belief space can affect the population component via an influence function. The influence function can affect population by altering the genome or the actions of the individuals.

The algorithm has been applied to find the optimum in a dynamic environment composed of mobile resources. The aim of this approach is to combine different knowledge sources to direct the decisions of the individual agents in solving optimization problems. Reynolds and collaborators developed an approach based on an analogy to the marginal value theorem in foraging theory to guide the integration of these different knowledge sources to direct the agent population (Reynolds et al. 2006a, b, c, 2008; Reynolds and Peng 2005; Stanley et al. 2014).

Cultural Algorithms were developed by Reynolds as a computational framework in which to embed social learning in an evolutionary context. Unlike traditional learning approaches, Cultural Algorithms derive their power from large collections of interacting agents. Within virtual worlds it is often the case that we wish to coordinate the behavior of large groups of intelligent agents in an efficient fashion. Cultural Algorithms are able to perform large-scale group learning within these virtual worlds. They have been used to generate socially intelligent controllers and group social behavior in various simulated environments, both serious and fun.

Given that the study of differences between animal and human behavior emphasizes human motivation and purposefulness and it affirms that human behavior is shaped first and foremost by an intention held by the subject, any historical explanation based only on the idea of "adaptation" seems to be limited (Stutz 2012). The same criticism is applicable to traditional "rational-choice" explanation where each agent individually assesses its situation and makes decisions based on a fixed set of condition-action rules (Gulyas 2002). That makes many agent-based models nothing more than a discrete planning for expressing descriptions of intended courses of action. It seems as if some designer (be a computer scientist or a god) needs to know the society before modeling it (Grand 2012).

Humans act supposedly on the grounds of beliefs about world-states that they contribute to modify, and which will be modified by their actions. Consequently, the "cause" of any social action that may have occurred in the past lies in the agent motivations for performing it. Social actions have been defined in terms of purposeful changing of natural and social reality (Leont'ev 1974; Engeström 1987; Wobcke 1998; Davydov 1999; Edwards 2000; Bedny and Karwowski 2004; Feldman and Orlikowski 2011; Thornton et al. 2012). Social actions are goal-directed processes that must be undertaken to fulfill some need or motivation. Therefore, they cannot be understood without a frame of reference created by the corresponding social motivation or intention. Leont'ev, one of the chief architects of activity theory, described social activity as being composed of subjects, needs, motivations, goals, actions and operations (or behavior), together with mediating artifacts (signs, tools, rules, community, and division of labor) (Leont'ev 1974). A subject is a person or group engaged in an activity. An intention or motivation is held by the subject and explains activity, giving it a specific direction. Activities are realized as individual and cooperative actions, and chains and networks of such actions that are related to each other by the same overall goal and motivation, which should not be considered as a mere condition for developing activity, but as a real factor influencing the actual performance of the action itself. A goal-directed action is under an agent's control if (1) the goal normally comes about as the result of the agent's attempt to perform the action, (2) the goal does not normally come about except as the result of the agent's action, and (3) the agent could have not performed the action (Wobcke 1998). For their part, actions consists of chains of operations, which are well-defined behaviors used as answers to conditions faced during the performing of an action. Activities are oriented to motivations, that is, the reasons that are impelling by themselves. Each motivation is an object, material or ideal, that satisfies a need. Actions are the processes functionally subordinated to activities; they are directed at specific conscious goals. Actions are realized through operations that are the result of knowledge or skill, and depend on the conditions under which the action is being carried out.

Goals, beliefs and intentions are in fact arbitrary interpretations of particular events (Bratman 1987). A particular course of action may be motivated in many cases in beliefs, represent the informational state of the agent. Using the term belief rather than knowledge recognizes that what an agent believes may not necessarily be true (and in fact may change in the future). These beliefs rest upon theories and these theories rest in turn on assumptions. Beliefs, the theories on which beliefs rest and the assumptions upon which theories rest must be valid if the means is to be considered right. Valid here means true if the belief bears on a representation of the world; and fair, good, legitimate in the case of should-be beliefs. Determining which means is right is not a trivial operation. Any belief is associated with reasons, but these reasons are often invalid for lack of access to relevant information, or because influenced by cognitive incompetence or of cognitive strategies, or due to the interference of conflicting goals (Boudon 2003). Correct beliefs result in sensible behavior; incorrect beliefs can cause unpredictable consequence actions. When we analyze our own behavior we are creating beliefs about our own goals. Desires represent the motivational state of the agent. They represent objectives or situations that the agent would like to accomplish or bring about. A goal can be described as a desire that has been adopted for active pursuit by the agent. Intentions represent the deliberative state of the agent—what the agent has chosen to do. Intentions are desires to which the agent has to some extent committed.

Nevertheless, the frontier between intentional activity and operational behavior is blurred, and movements are possible in all directions. Intentions can be transformed in the course of an activity; they are not immutable structures. An activity can lose its motivation and become an action, and an action can become an operation when the goal changes. The motivation of some activity may become the goal of an activity, as a result of which the latter is transformed into some integral activity. Therefore, it is impossible to make a general classification of what an activity is, what an action is and so forth, because the definition depends on what the subject or object in a particular real situation is. The constitutive elements of a belief cannot be precisely separated in the same way that two actors can be isolated from one another. Even when we separate one actor from another, the fact that his or her beliefs depend to a great extent on previously acquired knowledge means that he/she cannot be completely separated from the environment in which such knowledge has been acquired.

An additional trouble is that social motivations have their own dynamics, often contradictory. In other words, social activities are not isolated entities; they are influenced by other activities and other changes in the environment. People interact, influence others, reinforce some actions, interfere with others, and even sometimes prevent the action of other people (Creary 1981). The term contradiction is used to indicate a misfit within the components of social action, that is, among subjects, needs, motivations, goals, actions and operations, and even mediating artifacts (division of labor, rules, institutions, etc.), and produces internal tensions in apparently irregular qualitative changes, due to the changing predominance of ones over others. Activities are virtually always in the process of working through contradictions, which manifest themselves as problems, ruptures, breakdowns, clashes, etc. They are accentuated by continuous transitions and transformations between subjects, needs, motivations, goals, behavior, signs, tools, rules,