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

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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, community, division of labor, and between the embedded hierarchical levels of collective motivation-driven activity, individual goal-driven action, and mechanical behavior driven by the tools and conditions of action. Here lies the true nature of social causality and the motivation force of change and development: there is a global tendency to resolve underlying tension and contradictions by means of change and transformation. Since social activity is not relative to one individual but to a distributed collection of interacting people and the consequences of their actions, we cannot study how social activities took place by understanding the intentions or motivations of individual agents alone, no matter how detailed the knowledge of those individuals might be. To capture the teleological or purposive aspect of behavior, we should investigate collective action, that is, why different people made the same action, or different actions at the same place and at the same time. Its research goal should be to explain the sources or causes of that variability, and not exactly the inner intentions of individual action.

What we need to study is the constant interaction between agent and context. Consequently, the basic unit of motivation is not the discovery of some verbal proposition such as "*x* believes that *P*", "*x* desires that *P*", "*x* knows that *P*", and so forth. Rather, we are aware of those things that are playing a prominent role in constraining the global constraint satisfaction settling process in our minds (O'Reilly and Munakata 2002, p. 218). What constitutes "causality" is not just the "consciousness" of the reasoning system itself, but also the rich matrix of relations it bears to other agents, practices and institutions.

Beliefs, desires and intentions may change according to the variation in the local conditions, and according to what the agent may "learn" from its environment and from other agents interacting with it. To a certain extent, this is just giving the agents another level of rules. However, the nature of these rules is different, in that they are meta-rules about how to form rules (Lee and Lacey 2003). Such meta-rules allow for the type of self-reference that is key to the historical explanation. Individual social actors, in going about their various interactions, form representations of those interactions. Moreover, they abstract away from the details of individual interactions to formulate underlying rules that describe these interactions. In the case of societies, these rules are usually called norms or institutions. When individuals form abstractions about what the normative behaviors are in their society, they begin to act on them, either by behaving differently themselves or by reacting differently to the behavior of others. Thus, the abstractions the individuals make drive the behavior that emerges from their interactions. But the loop does not end here. As the individuals continue to interact based on the abstractions they have made and new societal patterns emerge, the individuals will make abstractions about those new patterns, which in turn will give rise to a new set of emergent behavior, ad infinitum (Baumer and Tomlinson 2006). Computational agents should be designed as learning entities, gaining ever more accurate information from the effects of their actions or more successful strategies from observing others' behaviors. In substance, reinforcement learning is shaped on the model of evolution, a fitness formula being always implied. This essentially has led to implement agents' capacity to gain more accurate information. But this is only part of the job required by a dynamic model of agent-hood. Agents undergo social influence, come to share the same beliefs and expectations, squeeze into the same practices, and this type of social influence sometimes leads them to form inaccurate, even wrong beliefs.

As a result of this focus on social actions as practiced by human actors in reference to other human actors, the idea of "agency" appears to be synonymous with an agent's way of being, seeing and responding in the world. It is an embedded and interpreting agency that draws on its funds of knowledge to both interpret and respond to the environment (Edwards 2000). The agent interprets and responds to the contexts of action and exploits the opportunities for effective action within them. It is an outward-looking mind which seeks local scaffolding to enhance its purposive action. However, it is not possible to fully understand how people act and work if the unit of study is the unaided individual with no access to other people. The unit of analysis is object-oriented action mediated by human produced tools and signs. Thus, we are constrained to study context to understand relations among agents, actions and goals. This is the reason of emphasizing the use of invariant change-relating capabilities to characterize historical events. What humans did and the way they did it is firmly and inextricably embedded in the social matrix of which every person is a member.

The obvious conclusion is that we are far from being perfect rational agents. And our ancestors even less, given the poor access to information at real time to take decisions (Leaf 2008). Nevertheless, we are very far from the current "stupidity" of usual computational agents in their eternal search for optimal but simple solutions.

Oestmo et al. agents' (Chap. 4) appear to be a bit more rational and less "adaptive" than traditional "optimal foragers". They know that they should produce tools to increase the possibilities of having success in hunting and gathering. This awareness on the necessity of technology is what makes them more "human" than strictly animal. They look for explanations of the changing raw material preferences when deciding to make tools. From a naturalistic point of view explanations for change in human raw material usage frequency would only include climate/environmental change and its co-variability with mobility and procurement strategies, the selection of certain raw materials for their physical properties, changes in demography, etc. All these parameters are well within a strong and limited rationality hypothesis, where prehistoric people, made optimal choices. But Oestmo et al. also consider the preference for appearance or color, symbolic value, and style. The authors have created a simple model of one forager with a mobile toolkit of fixed capacity that is randomly placed on the environment. The simulation is based on a previous model by Brantingham (2003). This "stupid but rational" behavior is compared to archaeological data from prehistoric settlements around the town of Mossel Bay, Western Cape, South Africa, offering a long sequence of change in raw material selection. Here, optimal decisions are not assumed, but tested against relevant prehistoric data. They think this is the right approach, instead of assuming the truth likeness of a particular theory of the way people made choices in a world with low developed means of production; we should look for particular tests of the explanatory power of the hypothesis. Oestmo et al. results should be compared with similar work by Davies et al. (2015), Clarkson et al. (2015), Pop (2015).

O'Brien and Bergh's agents (Chap. 6) are apparently even more "human", in the sense that the agents in their virtual world can build their own complex cognitive map of the environment around them, and they can make reference to ideological, social and political factor to motivate their decisions.

There is a growing interest in the computer science and artificial intelligence community to build more credible virtual agents that may act in a simulated world in the same way we believe humans would have acted. The belief–desire–intention software model (usually referred to simply, but ambiguously, as BDI, see Rao and Georgeff 1998; Wooldridge 2000; Luck et al. 2004; Bosse et al. 2011; Caballero et al. 2011; Taillandier et al. 2012; Kennedy 2012; Kim et al. 2013; Gelfond and Kahl 2014; Blount et al. 2014; Pantelis et al. 2016) is a software model developed for programming intelligent agents. In essence, it provides a mechanism for separating the activity of selecting a plan (from a plan library or an external planner application) from the execution of currently active plans. Consequently, BDI agents are able to balance the time spent on deliberating about plans (choosing what to do) and executing those plans (doing it). A third activity, creating the plans in the first place (planning), is not within the scope of the model, and is left to the system designer and programmer.

Alternative virtual agent architecture is "PECS" (Urban and Schmidt 2001; Malleson 2012) which stands for "Physical conditions, Emotional states, Cognitive capabilities and Social status". The authors of the architecture propose that it is possible to model the entire range of human behavior by modelling those four factors. PECS is seen as an improvement over BDI because it does not assume rational decision making and is not restricted to the factors of beliefs, desires and intentions (Schmidt 2000). Instead, an agent has a number of competing motives (such as "clean the house", "eat food", "raise children", "sleep" etc.) of which the strongest ultimately drives the agent's current behavior. Motives depend on the agent's internal state (an agent with a low energy level might feel hungry) as well as other external factors (an agent who smells cooking food might become hungry even if they do not have low energy levels). Personal preferences can also come into play, where some people feel a need more strongly than others even though their internal state variable levels are the same (Balke and Gilbert 2014). In this sense, Ho et al. (2006) have proposed a Categorized Long-term Autobiographic Memory (CLTM) architecture, utilizing abstracted notions of human autobiographic memory and narrative structure humans apply to their life stories (see also Pointeau et al. 2013; Lei et al. 2013; Bölöni 2014). El-Nasr et al. (2000) and Resisenzein et al. (2013) have explored the simulation of human emotions.

H-CogAFF cognitive architecture gives place to emotions and other high level cognitive layers integrating "fuzzy" boundaries between different levels of functionality, and allowing for some of the information-processing mechanisms to straddle two or more layers (Sloman and Christel 2003; Sloman 2011; Petters 2014; Goertzel et al. 2014).

Other recent essays in this direction are Goertzel et al. (2013), McRorie et al. (2012), Gratch et al. (2013), Faur et al. (2013), Kang and Tan (2013), Anastassakis and Panayiotopoulos (2014), Haubrich et al. (2015). For more advanced issues, see

Bostrom (2012), Hughes et al. (2012), Schönbrodt and Asendorpf (2011). Current work on cognition and artificial intelligence will allow the proper understanding of motivation in social action (Pollock 1995; Friedenberg 2011; Tenenbaum et al. 2011; Chella and Manzotti 2013; Diettrich 2014; Bryson 2015; Campennì 2016).

1.2.4 What Made Humans Really Human? Cooperation and "Collective" Action at the Dawn of Humanity

Certainly actual computational simulations of human behavior in the most remote past lack cognitive complexity. But this is not a source of troubles and problems, but a consequence of the emphasis on the generality and simplicity of human behavior and how the apparently unconscious repetition of simple actions produces the self-organized emergence of complex organization properties. This perspective should make us aware of the relevance of null models as a starting point of historical enquiry (Bocinsky 2014; Lake 2015; Cegielski and Rogers 2016). Bentley and Ormerod (2012) have argued for the utility of models which assume "zero-intelligence" on the part of agents to understand how far we can get with extremely simple social mechanisms and what must be added to them to explain social phenomena.

In any case, we do not think that the real problem of "intelligence" and "rationality" lies in the cognitive explicit content in the "mind" of each agent within the simulation. Obviously, we do not have in the present data about what men and women believed in ancient times. It is important to remember that we do not need to "recreate" the past as believed by people that lived then. It is the distance between our present problems and what happened in the past that motivates our emphasis on long term process and collective action instead of individual motivations. Probably this is not the case when studying a past situation that is relatively near to our present experience: the past desires of our grandparents and grandmothers may still constraint our decisions here and now. But there is no way that the desires of one person having lived more than 200 years ago can constrain what we want to do here and now. Therefore, when investigating the most remote past we are interested not in the individual but in collective action: what a population of a particular size made in the past can affect still what a new population that is a reproduction of the former one is able to do today (Oliver et al. 1985; Oliver 1993; Ball 2004; Iwanaga and Namatame 2002; Goldstone and Janssen 2005a, b; Miller and David 2013; Czaczkes et al. 2015; Will 2016). The negative side of this approach is that there is no possibility of knowing why an individual person made something somewhere at some moment. However, it does not presuppose the implicit randomness, subjectivity, or indeterminism of social action. The goal should be to explain the sources or causes of that variability, and not exactly the inner intentions of individual action.

The real issue is precisely that intentional actions of the individual agents give rise to functional, unaware collective phenomena. It is not that actual computer simulations ignore the basis of individual agency and that prehistoric people nor their computational surrogates were deprived of believes, desires and intentions beyond their direct survival (acquiring food), but social scientists are making emphasis on the analytical importance of understanding the roots of social self-organization before taking into account the role of the creative individual in a world constrained by unaware collective action. The fact that some characteristically human attributes are "mechanically" simple has been argued during the last 40 years. We do not need to affirm that prehistoric people were underdeveloped stupid people that acted like animals. Supposedly "modern" behavior like cooperation, alliance, technological innovations, etc. seems to be in fact the consequence of relative simple and plain mechanisms.

In this way, Janssen and Hill (Chap. 3) show how cooperation has a mechanical nature and, in some cases, it can be seen as adaptive. Fort et al. (Chap. 5) incorporate cultural transmission, that is, learning, to understand the speed of change in human populations during the Neolithic. They also argue that cultural transmission and economic change can be analyzed in adaptive and mechanical terms (although explicitly non-linear and non-monotonic) and not necessary the result of rational decisions nor cognitive states in the mind of agents.

Distributed computer simulation is one of the hallmarks for investigating this subjects given their ability to generate macro level behaviors caused by micro-level decisions of individual agents characterized by bounded rationality, decision-making autonomy, sociality, and dynamic interactions among them. According to that view the output of the social mechanism is a pattern of emergent behavior (self-organizing, collective behavior) which is difficult to anticipate from knowledge of the individual agents' behavior (Shoham and Tennenholtz 1997; Bedau 2003; Sawyer 2005; Neumann 2009; Helbing 2012; Helbing and Balietti 2013; Jennings et al. 2014; Schieve and Allen 2014; McHugh et al. 2016). For instance, any emergence of sociopolitical complexity should be considered as the resulting long and slow process produced by the model is generative, not deterministically hard-wired or causally pre-determined in any way (see Cioffi-Revilla and Bogle's contribution to this volume, Chap. 13). This reflection points to the necessary distinction between individual activity and their aggregated consequences, that is, between micro-motives and macro-behavior (Schelling 1978; Mella 2008). It is the same as distinguishing between agency and structure. In macro explanations, the set of individuals is viewed as a structure that can be characterized by a number of variables, whereas in micro motive explanation the structure is viewed as emergent from the interactions between the individuals. 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 agency.

A good example of the way of taking into consideration intelligence as a collective phenomenon rather than as the simple summation of individual abilities was Jim Doran's EOS system, probably the first computer simulation of historical events in the true sense of word (Doran and Palmer 1995a, b, Doran et al. 1994).

The idea was to explore a computational interpretation of growth of social complexity in the Upper Paleolithic period (around the time of the last glacial maximum) relating changing features of the natural environment to the emergence in the prehistoric past of centralized decision making, hierarchy and related social phenomena. The computational model investigated what could happen when “artificial” social agents with elements of human-like cognition shared a common environment, were strongly aware of one another and collectively performed hunting and gathering tasks to survive. Although very simple in their contents, the collective execution of agent plans implied that each individual plan affected the plans of other agents, and was affected by them in a recursive way. Then, by “observation” of which agent first acquired each resource, agents came to recognize particular resources as “owned” by particular agents or groups, and a form of territoriality could be displayed.

Doran’s model shows the consequences of cooperation at work and cultural transmission among hunter-gatherer systems. “Cooperation” is among the most analyzed causal factors for the modern understanding of “intelligent” decision-making in prehistory (Salgado et al. 2014). Current studies on cooperation as a social mechanism with relevant consequences for decision making are based on the effects of kinship and/or territoriality to reinforce the existence of social ties within clusters and to maintain group identity and shared practices. People have a preference for interacting with others who share similar traits and practices, which “naturally” diversifies the population into emergent social clusters. In the real world, as well as in a simulated world, individuals may display “in-group favoritism” (Hammond and Axelrod 2006), also called “parochialism” (Bowles and Gintis 2004; Koopmans and Rebers 2009; Fernández-Márquez and Vázquez 2014; Gintis et al. 2015; Santos et al. 2015; Salas-Fumás et al. 2016), in choosing how to interact, based on the advantages when interacting with “others” (according to individual or global beliefs). Especially relevant for this research is the possibility of simulating the social mechanism of Cultural Transmission as a form of social interaction (Reynolds et al. 2001; Mesoudi 2007; Roberts and Vander Linden 2011; Eerkens et al. 2013; Rorabaugh 2014, 2015; Clark and Crabtree 2015; Fort et al. 2015; Grüne-Yanoff 2015).

Analytically defining the consequences of cooperation according to the principle that “connected attracts” we make an important advance towards the explanation of apparently complex social behavior among small scale societies. More precisely, current simulations show that ethnicity can be understood in terms of the tendency of people with connected (or similar) traits (including physical, cultural, and attitudinal characteristics) to interact with one another more than with people unconnected (or dissimilar features). In addition, we can introduce the principle of social influence (i.e., the more that people interact with one another, the more similar they become) which runs at the level of communication and the formation of a socio-cognitive level. This influence process produces induced ethnicity, in which the disproportionate interaction of likes with likes may not be the result of a psychological tendency but rather the result of continuous interaction.

Computer simulation has allowed the discovery that social mechanisms that normally lead to cultural convergence—cooperation, influence and transmission—can also explain how population have diversified culturally through the ages (Read 2003, 2010). This conclusion is based on pioneer research by Axelrod (1997a, b). He proposed an abstract model based on the fundamental principle that the transfer of ideas occurs most frequently between individuals who are similar in certain attributes such as beliefs, education, social status, and the like. This study draws some interesting conclusions experimenting with different parameter configurations, including the non-intuitive result that the average number of stable regions formed decreases as the size of the territory increases. The resulting dynamics converges to a global monocultural macroscopic state when the initial cultural diversity is below a critical value, while above it ethnicity is unable to inforce cultural homogeneity, and multiethnic patterns persist asymptotically. This change of macroscopic behavior has been characterized as a non-equilibrium phase transition.

In any case, Axelrod's model is too simple to be used as an effective model of ethnogenesis. For instance, it has been proved (Klemm et al. 2003, 2005; San Miguel et al. 2005; Gracia-Lázaro et al. 2009) that if random noise is introduced at a low rate (allowing cultural traits to change randomly with a small probability), the basic dynamics of the ethnicity and influence model will drive the population away from cultural diversity and toward cultural homogeneity. This may happen because the introduction of random shocks perturbs the stability of cultural regions, eroding the borders between the groups. This allows the system to find a dynamical path away from the metastable configuration of coexisting cultural domains, toward the stable configuration of ethnogenesis.

Cultural drift raises the question of whether the above explanation of cultural diversity will hold if agents were permitted to make errors or develop innovations. Parisi et al. (2003), working also on the lineage of Axelrod's assumptions, have simulated a process of expansion of a single human group in an empty territory and looking at what happens to this group's previous culture when during the expansion process both cultural assimilation between neighboring sub-groups and random internal changes in the culture of each subgroup took place. By allowing multiplex influence, it is no longer possible for a deviant to lure its neighbors by influencing them one at a time. This strengthens the effects of ethnical homogeneity by insuring that agents can never be influenced in a direction that leaves them with less in common with their neighbors overall. If within-group interaction preference is the mechanism by which global convergence generates local diversity, then strengthening the tendency toward convergence might have the counterintuitive effect of allowing stable diversity to emerge. Parisi et al. show that Axelrod's result of no complete cultural homogenization is obtained even if we abandon the assumption that neighboring groups with completely different cultures cannot influence each other. In this expanded model not only assimilation is with the dominating culture of a site's entire neighborhood but, most importantly, there is no role of pre-existing cultural similarity as a determinant of cultural assimilation.

Instead of the exploration of a new territory by an ethnically homogenous population, Matthews (2008) has simulated the sudden arrival of a different ethnic group, and how it behaves with local populations. One might expect that in a culture with a very high rate of drift, new cultural regions may be absorbed very rapidly as common features may appear regularly by chance, facilitating interaction across boundaries. The results of this experiment suggest that despite such high levels of drift, distinct regions may persist for significant periods of time. In general though, it is possible to conclude that in relatively homogeneous cultures with low rates of cultural drift (as may be expected to be found in isolated, monoculture regions), any distinct cultures which do form are likely to persist for significant periods of time before being assimilated into the surrounding culture. These distinct cultures may appear through a number of possible mechanisms (including perhaps Axelrod's suggested local-interaction model), but an obvious example might be an invading or migrating group of people from a distant region with a very different culture. Finding aspects of culture in common with the invaders may be difficult, reducing the chances of further interaction and absorption. The second result suggests that even in a culture with a high rate of drift (such as a modern, fast-changing multicultural society) it may take a considerable amount of time for a new cultural group to integrate into its surroundings (Matthews 2008).

As ethnogenesis increases and activity restricts within the ethnically homogenous group, agents converge on their cultural characteristics; yet if there is enough heterogeneity in the population, this similarity among group members can also make them even more dissimilar from the members of other groups (Barceló et al. 2013a, b and 2015). Ultimately, this can produce cultural groups that are so dissimilar from one another that their members cannot interact across group boundaries. If cultural influence processes create differentiation between two neighbors such that they have no cultural traits in common, we should allow these individuals to alter the structure of the social network by dropping their tie and forming new ties to other individuals. Centola et al. (2007) have proposed a model where the network of social interactions is not fixed but rather evolves in tandem with the actions of the individuals as a function of changing cultural similarities and differences. The use of the level of heterogeneity in the population as a control parameter, allows to map the space of possible co-evolutionary outcomes and thereby show how network structure and cultural group formation depend on one another. These results address the question of how stable cultural groups can be maintained in the presence of cultural drift.

Contrary to Axelrod's claim, the effect of one cultural feature does not inherently depend on the presence or absence of others, but only so in dyadic relations where similarity matters. Boyd and Richerson (1987), McElreath et al. (2003), Heinrich and Heinrich (2007) have proved that if people preferentially interact in with people who have the same culture as they do, and if they acquire their markers and coordination behaviors by imitating successful individuals, groups distinguished by both norm and marker differences may emerge and remain stable despite significant mixing between them. Under such rules, within a group the behavior which is initially most common will reach fixation, as individuals with the less common behavior are less likely to receive the payoff. The successful behavior will also develop a marker associated with it as individuals sharing this marker will also be more likely to interact with each other and receive the higher payoff. These ethnically marked positions are examples of attractors within the model.

Some other important enhancements of Axelrod's model of the dissemination of culture includes: Barbosa and Fontanari (2009), Kim (2010), Bednar et al. (2010), Dutton et al. (2010), Lanchier (2012), Valori et al. (2012), Hawick (2013), Pfau et al. (2013), Kang et al. (2014), Gowdy and Krall (2015), Roos et al. (2015), Kovacevic et al. (2015), Upal (2015). Those research teams have constructed a diversity of computer models that allows the dynamic understanding of four hallmarks of culture: coordinated behavior, coherent cultural signatures, substantial within culture diversity, and cross cultural differences. In general, these approaches combine a social drive to coordinate with an individual desire for internal consistency. As a result, the formation of in-group favoritism in terms of the developing of a meaningful cultural signature implies that individuals within a community conform their behavior to match one another's, and also that there is some relationship that ties their behaviors and beliefs together from one activity or domain to the next, creating consistency across behaviors. In addition to conforming, people also choose to be around those who act as they do, what curbs group mergers because people avoid interacting with others who are not like themselves. Adding social influence to ethnogenesis exacerbates these effects: when individuals interact with others like themselves, and also actively become more similar to them, polarization between groups is even more pronounced. If individuals can use social markers to increase the likelihood of acquiring the behaviors adaptive in their context, markers and behaviors can become associated, and markers can in fact become exaggerated beyond initial differences between the populations.

A parallel approach has been Skyrms's study that patterns of coordinated behavior can best be explained from an adaptive dynamic perspective where the agents are only boundedly rational (Skyrms 2001). Skyrms concentrates on three mechanisms that can divert an abstract population of hunters from hunting hare on an individual disorganized basis to hunting stag and achieve a kind of collective equilibrium. The solutions are built on various *correlation* and *anti-correlation devices*. First, spatial and network embeddedness offer a correlation device that allows for the clustering of stag hunters (local interaction) and for efficient imitation, learning, and reproduction that all take place in the spatial or network locality. Second, these interactions change endogenously over time, such that network dynamics (due to partner selection) favors cooperation at the end. Adaptive dynamics operate on both strategy and interaction structure, which quickly shifts the balance in favor of cliques of stag hunters, without any kind of rationality assumed. Third, signaling and in particular signaling systems in which signals are not cheated and correctly interpreted can evolve and provide the solution towards equilibrium as collect ive action. Reinforcement learning helps to move coordination games to a signaling system in which signals are unambiguous (meaningful) with probability equal to one.

In this model rationality and common knowledge still play a role, although much less of it is required to explain game theoretical equilibria concepts than in standard motivations. The main problem is to give a convincing story of why agents will coordinate their behavior so as to establish a collective good. At first sight, social cooperation seems to be a prisoner's dilemma, or in the *n*-player case, a public goods game. In this game, by cooperating an individual helps all the other members of the group, but at a cost to himself. Therefore, a self-regarding player will never cooperate. It follows that social cooperation requires altruistic players—people must cooperate even though this is personally costly and the others alone benefit from one's prosocial behavior. It is easy to see why the public goods game is an allegory for social cooperation among humans. For instance, if we all hunt, if hunting is dangerous and exhausting, and we must share the kill equally, then a self-regarding hunter will prefer to shirk rather than hunt. Cooperation in this case requires altruistic hunters. Skyrms' point, however, is that if the game is repeated indefinitely, then cooperation among self-regarding agents is possible using what are known as "trigger strategies." A trigger strategy for a player is to cooperate as long as all other players cooperate as well. However, the first time one player defects, the trigger strategy dictates that all players defect on every succeeding round. It is easy to see that in this case, even selfish players will cooperate on all rounds, because the gains they have from defecting on one rounds may be swamped by the losses incurred by not benefiting from others' efforts on the succeeding rounds. The implication of Skyrms' position for social theory is quite dramatic. If he were correct, it would follow that humans could cooperate very effectively even if they were perfectly self-regarding, with absolutely no need for altruistic preferences, empathy, no predisposition for cooperating and sharing, nor any other prosocial behavior that goes beyond simple mutualism: An individual would help the group only as a byproduct of helping himself.

This is not the proper place to discuss the empirical validity of such ideas, but to insist in what can be done to understand the mechanical basis of collective action in terms of agent interaction. The model has been enhanced by Skirms and colleagues (Skyrms 2004, 2010, 2013; Huttegger and Skyrms 2013; Santos et al. 2008; Pacheco et al. 2011), and discussed critically by other authors (Bulbulia 2011; Starnini et al. 2011; Moreira et al. 2012; Tomasello et al. 2012; Wagner 2012; deBoer 2013; Song and Feldman 2013; Shaw 2015; Riebling and Schmitz 2016; Plikynas and Raudys 2016, among many others).

The idea of cooperation as a basis of cultural differentiation is resounding heavily in archaeology and anthropology. Madsen and Lipo (2015) have introduced an extension of the Axelrod's model of cultural differentiation in which traits have prerequisite relationships, and where social learning is dependent upon the ordering of those prerequisites. Their results point to ways in which archaeologists can build more comprehensive explanations of the archaeological record of the Paleolithic as well as other cases of technological change.

Phillips et al. (2014) test the hypothesis that the development of extra-somatic weapons could have influenced the evolution of human cooperative behavior. In their simulations, the authors found that cooperative strategies performed significantly better, and non-cooperative strategies significantly worse, under simulated weapons use. They conclude that the development of extra-somatic weapons throws new light on the evolution of human altruistic and cooperative behavior, and particularly 'strong reciprocity'. The notion that distinctively human altruism and cooperation could have been an adaptive trait in a past environment that is no longer evident in the modern world provides a novel addition to theory that seeks to account for this major evolutionary puzzle. With a stronger substantive goal, Shennan et al. (2015) have analyzed two distinct material cultures (pottery and personal ornaments) from Neolithic Europe, in order to determine whether archaeologically defined "cultures" exhibit marked discontinuities in space and time, supporting the existence of a population structure, or merely isolation-by-distance. They have investigated the extent to which cultures can be conceived as structuring "cores" or as multiple and historically independent "packages". More theoretical studies are those by Burtsev (2005), who has validated a model of cooperation based on the assumptions of heritable markers, constrained resource, and local interactions with the real data on aggression in archaic egalitarian societies, and Briz et al. (2014a, b), Santos et al. (2015) who suggest a model providing insight on how the spatial concentration of resources and agents' movements in the space can influence cooperation. Through carefully calibrating the model parameters with ethnoarchaeological data from ancient Patagonia fisher-foragers, the authors conclude that the emergence of informal and dynamic communities that operate as a vigilance network preserves cooperation and makes defection very costly. Also using ethnographical data on hunter-gatherers, Janssen and Hill (2014) have explored the implications of social living, cooperative hunting, variation in group size and mobility. Their simulations show that social living decreases daily risk of no food, but cooperative hunting has only a modest effect on mean harvest rates. This research is related with their results in Chap. 3 in this book.

Savarimuthu et al. (2011b) use an agent based model to simulate a hunter-gatherer society where the norms of the society are affected by changing environmental conditions. In particular, the authors are interested in exploring how norms might change in a society based on the changes to the type of resources available in the society. Also based on ethnoarchaeological data to calibrate empirically the model parameters, Barceló et al. (2013b, 2015) have simulated how small sized groups (less than 10 households) died by starving because the impossibility to build a high enough number of social ties. Given that the probabilities of interaction and labor exchange are conditioned on the existence of some shared belief elements, agents should be able to adapt their identity in response to the identity of agents with them they have arrived to cooperate successfully. Cultural consensus is built adaptively from the communalities among individual identities of agents connected at a precise time-step. The higher the interaction, the higher identity likelihood. It is also assumed that the higher the perceived similarity in reference cognitive models (social memory), the higher the probabilities of cooperating and creating social aggregates conditioning social reproduction and how individual identities are transmitted to new generations.

Consequently, the study of intentionality in the remote past is not a question of individual “intelligence” or “rationality”. The examples here quoted contribute to sustain the view that prehistoric people did not die as often as imagined as a direct consequence of scarcity. Instead of the traditional image of prehistoric hunters fighting for survival in hard environments, modern research based on computer simulation suggests that social exchange networks were easy to build and negotiate, allowing hunting success even in the case of low availability of resources and the poor efficacy of working instruments (Younger 2003, 2004; Ladefoged et al. 2008; Helbing et al. 2011; Gurven et al. 2012; Neumann and Secchi 2016).

This explanation is based on the assumption that “cooperation” when survival is not individually attained implies an investment in labor that produces a common benefit. Such investment comes from agents whose survival has been effectively attained individually, and it is produced at no cost, because there is no surplus accumulation beyond the survival level. The benefit is not only individual (some agents survive thanks to the help of others), but also common: a social aggregation emerges allowing technological diffusion and increasing a cultural consensus which can be necessary in the future. In that sense, positive interaction is not only the result of bounded rational decision making, but it is filtered by the specific social (cultural) identity of agents, a parameter that changes constantly because it is probabilistically conditioned by a number of social factors. Among hunter-gatherers, positive interaction depended on the predictable benefits of working together and sharing the results of collective work. The higher the interaction, the higher the probability of hunting success. It is not the same as arguing that the higher the number of hunters, the higher the amount of meat. In some scenarios, the total amount of energy per person can be lesser, but hunting success is more frequent in the long run, that is, it is more probable. In the usual circumstances of small bands with hardly efficient instruments for hunting and transport, the absence of cooperation made uncertain the probability of survival, given the increasing risk for hunting failure, even in the case of high animal availability in the area.

In this line of research, making emphasis on “collective” decision making, rather than on optimal rationality we can mention current work on technological change and innovation. Prehistoric people were not rude savages without any idea or necessity for innovate (Mithen 1990, 1991), rather they experimented constantly new materials and new abilities to expand their technology and increase the success of hunter and gathering activities needed for survival. Innovation was not the result of the individual geniality of a very clever man, “inventing” for his community. It was a collective phenomenon of experimentation and the higher probability of adopting some new tools or behaviors and rejecting others.

In a recent simulation of prehistoric hunter and gatherer populations from Patagonia (the southernmost part of South America), Barceló and colleagues have created an artificial world in which subsistence was obtained by individual households by means of labor with the contribution of its own technology, whose efficiency was estimated according a parameter that range from 0.01 to 2. High efficiency indicates that all local resources can be managed independently of its difficulty of acquisition given the extreme performance of available technology. Low values are characteristic of human groups with hardly evolved instruments, in such a way that only a part of locally available resources are effectively managed. The efficiency of food preservation techniques is another technological factor, related with the overall level of development of means of production. Both factors —quantity of people to work and technological efficiency act upon the difficulty of acquiring and transforming resources into subsistence and hence on survival. But technological efficiency is not a fixed parameter; it changes because hunter-gatherers learn from others in the environment different ways of making tools. They compare the new tools when they cooperate and adapt some characteristics—but not all—from most successful hunters (Del Castillo et al. 2014; Barceló et al. 2015). The result is an *S*-shaped curve of technological innovation that exactly reproduce modern mechanisms of technological change. This characteristic model can be understood as the number of adopters of a new technique or tool rises slowly at first, when there are only few adopters in each time period. The curve then accelerates to a maximum until half of the individuals in the system have adopted. Then it increases at a gradually slower rate as fewer and fewer remaining individuals adopt the innovation. The *S*-shape of a typical development curve can be viewed as the result of the process of exhausting a 'solution space' of potential improvements: as the pool is explored and exploited there are fewer and fewer improvements remaining to be discovered, slowing the pace of improvement if the number of trials stays the same. Again, the *S*-curve is produced in a setting where there is a finite potential for improvement. This result call for the resemblance between the process of technological change and innovation in the most remote past and the immediate present. Innovations to hunting equipment and storing technology followed similar trajectories as hybrid corn among Iowa farmers, bottle-feeding practices among impoverished Third Worlders, new governance practices among Fortune 500 companies, chemical fertilizers among small-scale farmers, and the practice of not smoking among Americans. "Intelligence" of prehistoric people was like "intelligence" of our contemporaries (White 2008).

Creating a generative model of technological change is an interdisciplinary effort that should include researches in various fields, like demography, anthropology, paleo genetics, and human ecology. Important questions that should be addressed before we can quantify the parts of a population adopting an innovation or changing their cultural features include the establishment of methods for inferring past population structure, the timing of the adoption or change, the relative importance of demographic variations, and the possibilities of alternative hypotheses like demographic transitions, colonization events, and/or population extinctions. Among current computer simulations along this lines of research, we can mention Heinrich (2001), Ma and Nakamori (2005), Dawid (2006), O'Brien and Bentley (2011), Rush (2011), Zenobia and Weller (2011), Kiesling et al. (2012), Vespignani (2009, 2012), Boyd et al. (2013), Laciana et al. (2013), Papachristos et al. (2013), Nan et al. (2014), O'Brien et al. (2015), Porčić (2015), Spaiser and Sumpter (2016).

1.2.5 *The Myth of the Good Prehistoric Savage: The Origins of Social Differentiation and Complexity*

An obvious consequence of this way of considering social organization as an emergent property of the mechanisms of cooperation (or the lack of it) and cultural transmission, is that the origins of social diversity, hierarchy and complexity can also be considered as emergent properties of relatively basic social mechanisms. Caldas and Coelho (1999) have argued that what we call today "institutions" were in fact solutions to recurring problems of social interaction in small-scale societies, and should be understood as preconditions for social life, unintended outcomes, and human devised constraints.

If for 99 % of its history humanity lived forming small scale, "egalitarian" communities, why those early undifferentiated groups diversified and coercion, power, inequality and hierachization have marked social evolution? First of all, what is "social complexity"? We should approach this term in the sense of a conceptual framework and not as a particular kind of society. The idea of complexity refers to phenomena with many parts and many possible arrangements of the relationships between those parts. Herbert Simon was one of the seminal thinkers in the study of complexity and also on computer simulation and artificial intelligence. In 1962, he put forward several key ideas: "(…) roughly, by a complex system I mean one made up of a large number of parts that interact in a no simple way. In such systems, the whole is more than the sum of the parts, not in an ultimate, metaphysical sense, but in the important pragmatic sense that, given the properties of the parts and the laws of their interaction, it is not a trivial matter to infer the properties of the whole. In the face of complexity, an in-principle reductionist may be at the same time a pragmatic holist. (Simon 1962: 468). Therefore, when we are speaking about social complexity we are speaking on the internal differentiation of subgroups of people within a well-defined group, and the existence of differentiated patterns of relationships or arrangement among those subgroups.

An important corollary to the very definition of complexity in social groups is that the behavior of the complex social system is difficult to predict because of the no simple interactions among the constituting social sub-groups. In a complex system we cannot provide a simple aggregation model of the system that adds up the independent behaviors of the parts; rather, the parts are influenced in their behaviors by the behaviors of other components. The state of the social system is fixed by the interdependent dynamics of agents and groups of agents; which implies that collective behavior can oscillate wildly with apparently similar initial conditions.

Cultural evolutionists usually speak of human societies evolving toward greater complexity or higher degrees of organization. This is an important aspect of any historical investigation. Is social inequality an immutable result of the destiny of any agglomeration of people, or the emergent consequence of the interaction between individuals and groups of individuals (households, communities, tribes, territories, etc.)? The increase in complexity in the course of social evolution that can be observed in historical terms is, however, neither inevitable nor universal. There is no reason to regard the evolutionary process as one of inevitable progress, nor is an increase in complexity of human societies inevitable (Nowotny 2005; Dundes and Harlow 2005; Anderson et al. 2014; Vanhée et al. 2014; Neumann and Secchi 2016).

If we equate social inequality with the formal definition of disorder, we would implement a computer model of social evolution in terms of an evolution from order—hunter gatherer intrinsic egalitarianism—to disorder—economic inequality, exploitation, social and political hierarchy and class struggle-. In physics, the terms order and disorder designate the presence or absence of some symmetry or correlation in a many-particle system. The strictest form of physical order in a solid is lattice periodicity: a certain pattern (the arrangement of atoms in a unit cell) is repeated again and again to form a translationally invariant tiling of space. Lattice periodicity implies long-range order: if only one unit cell is known, then by virtue of the translational symmetry it is possible to accurately predict all individual (atomic) positions at arbitrary distances. A system is said to present disorder when some parameters defining its behavior are random variables, that is, when not all components have the same values, and the distribution of values does not follow a regular pattern. This is also characteristic of societies defined in terms of the unequal character of access to means of production, coherence and social and political hierarchy: some agents are more powerful than others are because they influence decisively in the economic and social reproduction decisions they are able to take. There is not a single type of complex societies, but different degrees of internal differentiation.

Nature tends from order to disorder in isolated systems. That means that "disorder" is a more probable state of any system than order. Its measure is often called entropy (Kubat and Zeman 1975). The mathematical basis with respect to the association entropy has with order and disorder began, essentially, with the famous Boltzmann formula, $S = k \ln W$, which relates entropy S to the number of possible states W in which a system can be found. In the case of social systems, the entropy of a collection of social agents within the system can be defined as a measure of their disorder or equivalently, how close a system is to equilibrium—that is, to perfect internal inequality. A more precise way to characterize social entropy is in terms of the different number of diverse arrangements along a given temporal trajectory. Thus, an increase in entropy means a greater number of microstates for the final state than for the initial state, and hence more possible arrangements of a system arrangement at any one instant. Here, a greater 'dispersal of the total energy of a system' means the existence of many possibilities (Lambert 2002).

Annila and Salthe (2009), among many others (see also Tesfatsion 2003; Deguchi 2011), have regarded economic activity as an evolutionary process governed by the 2nd law of thermodynamics. The universal law, when formulated locally as an equation of motion, reveals that a growing economy develops functional machinery and organizes hierarchically in such a way as to tend to equalize energy density differences within the economy and in respect to the surroundings it is open to. Diverse economic activities result in flows of energy that will preferentially channel along the most steeply descending paths, leveling a non-Euclidean free energy landscape. This principle of ‘maximal energy dispersal’, equivalent to the maximal rate of entropy production, gives rise to economic laws and regularities. The law of diminishing returns follows from the diminishing free energy while the relation between supply and demand displays a quest for a balance among interdependent energy densities. Economic evolution is dissipative motion where the driving forces and energy flows are inseparable from each other. When there are multiple degrees of freedom, economic growth and decline are inherently impossible to forecast in detail. Namely, trajectories of an evolving economy are non-integrable, i.e., unpredictable in detail because a decision by a player will affect also future decisions of other players. We propose that decision making is ultimately about choosing from various actions those that would reduce most effectively subjectively perceived energy gradients.

Social structure is a common phenomenon in nature, and it is not a necessary characteristic of human “intelligence” or rationality. Specifically, many species of the order of primates show different patterns of “complex” social structure. The limits of collective action and the emergence of patterns of social affiliation and differentiation in primate societies have been recently simulated (Bryson et al. 2007; Puga-Gonzalez et al. 2009, 2014; De Vries 2009; Evers et al. 2011, 2012; King and Sueur 2011; Sueur et al. 2011; Dolado et al. 2014; Smith et al. 2016; Will 2016). For instance, Witkowski and Ikegami (2016) have created a virtual world in which agents progressively evolve the ability to use the information exchanged between each other via signaling to establish temporary leader-follower relations. These relations allow agents to form swarming patterns, emerging as a transient behavior that improves the agents’ ability to forage for the resource. Once they have acquired the ability to swarm, the individuals are able to outperform the non-swarmers at finding the resource.

The basis for many of those studies is a model for the origins of domination in animal populations proposed by Hemelrijk (1999, 2002, 2004), Hemelrijk et al. (2005). In this virtual world, artificial entities live in a homogeneous world and only aggregate, and upon meeting one another and may perform dominance interactions in which the effects of winning and losing are self–reinforcing. Whether an agent will initiate an attack depends on the chance it has to defeat its opponent. If the risk of losing is large the likelihood that the agent will start an attack is small (‘risk-sensitive attack strategy’). When a dominance interaction actually takes place the outcome of the fight is decided probabilistically by the relative win chance. Defeating an opponent having a small probability to win increases the winner’s dominance value less than defeating an opponent that has a large probability to win (‘damped positive feedback’). The ordering of the agents according to this hypothetical value can be read as the emergence of a ‘real hierarchy’. The agent’s DOM value is intended to correspond with a real animal’s capacity to win fights. By varying the intensity of aggression only, one may switch from egalitarian to despotic virtual communities. In addition, artificial despotic communities show a clearer spatial centrality of dominants and, counter–intuitively, more rank overlap between the sexes than the egalitarian ones. Because of the correspondence with patterns in real animals, the model makes it worthwhile comparing despotic and egalitarian species for socio–spatial structure and rank overlap too. Furthermore, it presents with parsimonious hypotheses which can be tested for patterns of aggression, spatial structure and the distribution of social positive and sexual behavior.

To sum up, violence and revenge may reduce the survival probability of the population. Flight from known aggressors enhanced the survival of the total population, at the expense of social cohesion. These examples show the possible role of violence and aggression on the evolution towards increasing social complexity (see also Ilachinski 2004; Taylor et al. 2004; Clements and Hughes 2004; Younger 2005, 2011; Lim et al. 2007; Philips et al. 2014).

Rather than an unconscious solution to instinctive violence, we may suggest that it was the rational and conscious emergence of social norms constraining free will what characterized social evolution and the development of more complex social systems (Savarimuthu et al. 2011a). It has been suggested that social norms help people self-organizing in many situations without relying on a centralized and omnipresent authority (Villatoro and Sabater-Mir 2009; De la Cruz et al. 2012; Vila et al. 2013. See also Makowsky and Smaldino 2015; Roos et al. 2015; Gelfand and Jackson 2016; Horiuchi 2015; Santos et al. 2016; Thürmel 2016). On the contrary to institutional rules, the responsibility to enforce social norms is not the task of a central authority but a task of each member of the society (Ghorbani and Bravo 2016).

Castelfranchi et al. (1998) suggested the need of a social norm prescribing: "attack an eater unless the food item being eaten is marked as 'owned' by that agent". The multi-agent system is composed out of two different sub-populations: agents either respect the finder-keeper precept (the Respectful) or not (the Cheaters). Either through experience or through communications the agents learn whether another agent is a Respectful or a Cheater. The 'normative' algorithm of the Respectful is modified so that they respect the norm only with agents known to be Respectful. This looks like a sanction towards the Cheaters, but as the finder-keeper precept does not hold for any Cheater—it is in fact not prescribed for them—they cannot violate it, and therefore they cannot be sanctioned. The Cheaters are defined as non-normative, i.e., self-interested agents. In this respect, in the Castelfranchi, Conte and Paolucci model, it is the Respectful who violate the finder-keeper norm if they do not respect the Cheaters. It is rational that the Respectful only respect themselves, but how do we know, that decisions about the respect or disrespect of norms are the result of a rational calculus? Is it rational that the Cheaters always disrespect the finder-keeper norm? Under the title of deviant behavior, there is a long research tradition in sociology that investigates the reasons for a lack of respect of norms, which could advance theory construction here. Working on the results of this model, Saam and Harrer (1999) have studied the hypothesis, which can be traced back to Marx, stating that the "finder-keeper" norm while controlling aggression efficaciously reduces social inequality holds only in quite egalitarian societies. Throughout a variety of non-egalitarian societies, it instead increases social inequality. The authors have remodeled the model's normative behavior from a sociological point of view by implementing Haferkamp's theory of action approach to deviant behavior, demonstrating that it is possible to integrate power into computational models of norms.

Gavrilets (2012) shows that the differences in fighting abilities lead to the emergence of hierarchies where stronger individuals take away resources from weaker individuals and, as a result, have higher reproductive success. He has shown that the logic of within-group competition implies under rather general conditions that each individual benefits if the transfer of the resource from a weaker group member to a stronger one is prevented. This effect is especially strong in small groups. This effect can result in the evolution of a particular, genetically controlled psychology causing individuals to interfere in a bully–victim conflict on the side of the victim. A necessary condition is a high efficiency of coalitions in conflicts against the bullies.

Ray and Liew (2003) adopt a different approach by assuming that leaders are the better performing individuals that help others in the society to improve through an intrasociety information exchange. "Better" may refer to different behaviors: more successful in hunting or sharing resources with others, more efficient in fighting against violence and aggression, etc. Such "leaders" would improve only through an intersociety information exchange that results in the migration of a leader from a society to another that is headed by better performing leaders. This process of leader migration would halve helped the "better" performing societies to expand and survive where others disaggregate and disappear.

Hazy (2008) defines leadership as those aspects of agent interactions which catalyze changes to the local rules defining other agents' interactions. According to this author, there are five distinct aspects of leadership to be observed. Leadership involves actions among agents that: (a) identify or espouse a cooperation strategy or program, (b) catalyze conditions where other agents choose to participate in the program, (c) organize choices and actions in other agents to navigate complexity and avoid interaction catastrophe (sometimes called "complexity catastrophe"), (d) form a distinct output layer that expresses the system as a unity in its environment, and (e) translate feedback into structural changes in the influence network among agents. Leadership in all of its aspects serves three functional demands in supporting the purposes of participating agents and groups of agents. Generative leadership identifies and generates variety in the programs of action, resources and capabilities available to the community. Convergent leadership increases the perceived benefit to cost ratio of participating in a program of action; this deepens and makes less rugged the attractor basin associated with agents choosing to adopt a particular program of action. Unifying leadership promotes collective identity, or "unity," and catalyzes actions and communications that pressure others to conform to a program; it clarifies boundaries and enables increased participation and cooperation at the margin within an attractor basin. See also Boal and Schultz (2007) about this view on "strategic" leadership.

Accepting dominance and creating institutionalized forms of leadership has been considered as an answer to conflict (Spisak et al. 2011). Particular attention has been given to the role of the "follower" and the specific pressures encouraging "followership investment" and the emergence of traits intended to signal potential leadership ability. This is a source of internal differentiation, and hence of "complexity" as leaders differentiate from the rest of the population. Eguiluz et al. (2005) have created a virtual world in which leaders are individuals getting a large payoff who are imitated by a considerable fraction of the population, conformists are unsatisfied cooperative agents that keep cooperating, and exploiters are defectors with a payoff larger than the average one obtained by cooperators. The dynamics generate a social network that can have the topology of a small world network. The network has a strong hierarchical structure in which the leaders play an essential role in sustaining a highly cooperative stable regime. But disruptions affecting leaders produce social crises described as dynamical cascades that propagate through the network. "Prestige" increases the different nature of leaders, coming into existence to signal the level of skill held by their owners, in order to gain deference benefits from learning individuals in exchange for access.

Clemson and Evans (2012) have simulated a virtual world in which agents can choose to follow the choices made by a neighbouring agent in a social network (the future "leader"). The authors investigated three different types of possible social network (the Erdős–Rényi random graph, the scale-free network, and the regular-ring network), chosen to represent various extremes in terms of their substrate degree distributions, and investigated each using a variety of network sizes. Results highlight the apparently universal aspects of social behaviour. This universal form shows that, irrespective of the type of underlying social network, the leadership structure which emerges has an initial power-law section. That is, there are always a few agents whose actions are copied by many others. However, the authors have also found that the nature of the social network linking agents does have a significant effect on the 'fatness' of the leadership distribution. The virtual abstract worlds investigated here are clearly not realistic in many senses, but they can capture some of the basic features of competition dynamics thorough history. It is clear that the copying of strategies from a local social neighbourhood does lead to the emergence of a leadership structure, regardless of the nature of the social network.

Among the agent-based models that explicitly take into account social inequality and conflict, we can mention Smith and Choi (2007), who have simulated the emergence of inequality in small-scale societies. The model is predicated on the assumption that a limited number of asymmetries, such as differential control over productive resources, can explain the emergence of institutionalized inequality. They also draw on contemporary evolutionary theory in order to avoid the pitfalls of naïve functionalism and teleology. Their approach is not to deny any possibility of collectively beneficial outcomes or directionality to sociopolitical evolution, but rather to show how it emerges from the interaction of individual agency, social structure, and environmental constraints. In their computer simulation, some agents (depicted as "Patrons") control limited areas with greater per capita resource endowments, and can trade access to these for services from less fortunate agents (depicted as "Clients"). There is also an additional set of isolated agents which simply defend richer patches for their exclusive use, while others (depicted as "Doves") share any resources on their patch with other non-territorial agents (Doves or Clients). In the initial simulation, all agents are Doves, randomly distributed over a heterogeneous environment, so each agent has different probabilities to become a Patron or a Client depending on its behavior and the productivity of the area it is placed. Under default parameter values, non-territorial strategies dominate, split equally between Dove and Client types, and isolated and Patron types are about equally represented in the remaining areas. However, a stable patron-client regime emerges in about one third of all runs, and takes over the population about 10 percent of the time. Obviously, environmental heterogeneity is critical, as Patrons capitalize on their relatively rich patch endowments to participate in exchanges with Clients, and hence variation in property endowment, provides the initial opportunity for the emergence of inequality. Yet this is not sufficient, nor can this be glossed as "environmental determinism", since alternative strategies, interacting with similar resource heterogeneity do not generate socioeconomic inequality. Demographic parameters have also a strong effect on the relative success of territorial and non-territorial strategies. When mortality is high or reproductive rate low, the initial (all-Dove) population expands slowly so that isolated and Patron agents are able to spread and control rich patches, effectively keeping Dove and Client numbers low at equilibrium. Conversely, low mortality or high reproductive rate allows Doves to proliferate rapidly, and territorial agents are locked out (with Clients arising in modest numbers through mutation and drift). Increased mutation rates are favorable to the spread of Client and Patron strategies, but only because this retards the initial proliferation of Doves.

Although this model may be considered as too restricted and limited, it allows exploring the hypothesis that a limited number of asymmetries can explain most cases of emergence of institutionalized inequality through history, specially in ancient times. These might include asymmetries in control over productive resources, control over external trade, differential military ability (and resultant booty and slaves), or control of socially significant information. As simulations suggest, these asymmetries need not be employed coercively, as long as they are economically defensible and can provide an advantage in bargaining power sufficient to allow the concentration of wealth and/or power in the hands of a segment of the social group or polity. The modeling indicates that such asymmetries can be self-reinforcing, and thus quite stable to moderate perturbations over time. Because most of the social transactions based on them are mutual rather than coercive, it can be suggested that such systems are likely to be more stable than the stratified social systems (e.g., nation states) that eventually succeed them.

Dwight Read (2002, 2003) has followed a very similar approach and shows how competition is shown to play a critical role in the way interaction—among decision-making, demographic parameters, and social units that organize resource ownership and procurement—either promotes or inhibits change in social organization.

Koykka and Wild (2015) have simulated how group dispersal may be initiated by leaders. The authors use a theory of inclusive fitness to examine the incentives for leading and following in this context. High relatedness, significant reductions in the cost of dispersal due to dispersing in groups, and reproductive skew in favor of followers facilitates the emergence of group dispersal. In contrast to some previous theoretical work, which has either concluded that leadership is uniformly altruistic or that it is uniformly selfish, this investigation suggests that at evolutionary equilibrium the incentives for leading can be either selfish or altruistic. The nature of result (selfish or altruistic) depends on ecological and social conditions such as the cost of dispersal and the relatedness between leaders and followers. The model demonstrates that kin selection is sufficient and that individual differences in condition and ability are not necessary to promote the emergence and maintenance of leader–follower relationships. It has been suggested (Layton et al. 2012) that band formation evolved in humans from the more transient fissioning behavior as a solution to the conflicting pressures of sustaining higher levels of cooperation required in hunting and the division of labor in a more dispersed community. If disputes break out, or if resources in the band territory are temporarily depleted, the existence of a wider community continues to be adaptive. Van der Post et al. (2015) have studied the evolutionary progression from “leader-follower” societies to “fission-fusion” societies, where cooperative vigilance in groups is maintained via a balance between within- and between-group selections. Group-level selection can be seen as generated from an assortment that arises spontaneously when vigilant and non-vigilant agents have different grouping tendencies. The evolutionary maintenance of small groups, and cooperative vigilance in those groups, is therefore achieved simultaneously. The evolutionary phases, and the transitions between them, depend strongly on behavioral mechanisms.

An obvious consequence of the emergence of leader-follower dominance relationships is the signaling of this difference, that is, the origins of prestige as a way to express hierarchical difference. Plourde (2008) argues that strategies towards signaling social difference can invade a non-signaling population and can be evolutionarily stable under a set of reasonable parameter values. Increasing competition levels can be likely the selective force driving the adoption of this novel strategy. Two changes in the social context in which prestige processes operate have been also tentatively identified as leading to increased levels of competition for prestige: (1) increasing group sizes and (2) increasing complexity or size of the existing cultural repertoire (see also Reyes-García et al. 2008; Heinrich 2009; Bentley et al. 2011; Halevy et al. 2012; Cheng et al. 2013). Similar approaches are being considered for analyzing social evolution from egalitarian human communities to “complex” and internally diversified human groups with complex interaction links between groups hierarchically organized (Pauketat 1996; Cohen 1998; Walby 2007; Heinrich and Boyd 2008; Helbing 2012; Hoffrage and Hertwig 2012; Edmonds and Meyer 2013; Hofstede 2013; Perch et al. 2013; Gavrilets and Fortunato 2014; von Rueden 2014; Skyrms 2014).

But conflict, violence and domination are not the only sources of social diversification and the increase of social entropy in small scale societies with scarce development of their means of production (hunter-gatherer societies). Empirical evidence suggests that division of labor in animal societies is positively related to group size. Frolova and Korobitzin (2002), Robinson-Cox et al. (2007) and Dyble et al. (2015) have simulated the emergence of gender stratification in artificial societies of hunter-gatherers. Jeanson et al. (2007) have simulated how group size influences division of labor using a fixed response-threshold model. They have investigated how expected by-products of increased population size, including demand (total work need relative to total work force available) and task number, affect this relationship. Their results indicate that both low demand and high task number positively influence division of labor. If social division of labor is an emergent property of group size and the need of increasing productivity, Bentley et al. (2005) have explored how an exchange network coevolves with the changing specializations of the agents within it. Through simulation, the authors keep track of who is connected to whom through a mapping of the network and the specializations of each agent, and they test the effects of simplified individual motivations for exchange, the make-up of the initial population of agents, and abstract representations of basic ideological dispositions such as the belief in private ownership. The aim was to test whether specialization and wealth inequalities are natural, self-organizing qualities of a small-scale economy. Internal differentiation can emerge, even in the absence of conflict, violence and the needs of protection (see also Crabtree 2015). Chiang (2015) argues that the way inequality evolves as a result of egalitarian sharing is determined by the structure of “who gives whom”: social networks make a difference in how egalitarian sharing influences the evolution of inequality.

Social structure is an emergent property of a group of individuals; it cannot be the property of any single agent. Explanations for the evolution of complex societies assume that the organizational benefits of complexity are the reason it evolves (Edmonds et al. 2009). Among others, Rosenberg (2009) proposes that complexity is a product of group selection. He suggests that the organizational benefits are exaltations, built on authority only after it already exists, and which first develops to provide a more primitive benefit, conflict resolution. He further argues that in contexts where the maintenance of group unity confers a net top-down advantage to an egalitarian group’s members, even after factoring in loss of personal autonomy, egalitarian ideology will be abandoned and replaced by hierarchical ones.

It is obvious that much more research is needed in this area, not only as developments of abstract social theory, but computer simulations calibrated with historical data in well-defined scenarios (see later, Sect. 1.2.6).

1.2.6 Simulating Economic, Social and Cultural Change in Prehistory. Why Humans Have Made Life so Complex and Difficult

Cultural diversity, social division of work and social hierarchization can be studied in terms of the complex (non-linear) accumulative consequence of relatively simple social mechanisms acting along time on non-isolated and dynamic aggregates of social agents. Therefore, we can explore computationally the study of cultural shift and change (Read 1987; Kondrashin 1997; Frantzeskaki et al. 2008; Xu et al. 2013; Sanders 2015). The span of this definition of cultural shift comprises from technical or technological changes, the development of means of production, the emergence of new social structures, the adoption of a different set of political tires, the transformation of religious beliefs, the adoption of a new language by a society, etc. (Weidlich 2002; Bentley et al. 2004; Bergman et al. 2008; Schilperoord et al. 2008; de Haan and Rothmans 2011; Holtz 2011; Safarzynska et al. 2012; Kandler and Shennan 2013; Zeppini et al. 2014; Carrignon et al. 2015; Nicholson and Sibani 2015; Marsh 2016).

Isern and Fort contribution to this volume (Chap. 7) focus on a specific kind of cultural shift: language shift. The birth of a new language is a slow process which usually includes several successive minor processes that spread throughout the population over the course of millennia, until eventually the language has diverged enough from the original language as for them to be mutually unintelligible. These are often considered random processes, analogous to genetic drift, which may include the invention of new words—e.g., for innovations—, acquisition of loan-words from other languages in contact, phonetic changes. The other process of language shift, the displacement of the local language by a foreign one that becomes the new prominent language in the region, once started, is usually a much faster process, which can take place in as short a time as a single generation. The authors present a language competition model devised to predict the evolution of the number of speakers when an external language is displacing the native one. In the model, the authors are interested especially in language displacement processes which do not imply large movements of people or even population substitution. Isern and Fort mathematically model the progress of a linguistic frontier over time and space, when the displacement mechanism is due to language acquisition rather than population substitution, with a reaction-diffusion model similar the wave of advance models (see Fort et al., Chap. 5, this volume), that is, a model where cultural shift is simplified to increase or decrease in the population number due factors such as population growth or conversion into another population group. For a review of historical linguistics simulation see: Cangelosi and Parisi (2002), Steels (2011), Steiner et al. (2011), Gong and Shuai (2013), Martins et al. (2014).

Beyond language evolution, the study of social transitions comprises global changes with crucial impact on the evolution of human history, which besides the technical changes directly related to the adoption of agriculture, entailed as well changes in using organization, social structures and belief systems that may be the initial seed of the present sociocultural organization. The adoption of agriculture, herding and stockbreeding is one of the traditional domains for understanding the complex dynamics in cultural shift. Archaeologically known as the Neolithic, in this period human populations began to produce their own food substituting predator and forager practices that were in use for the most part of human history. There are many hypotheses about why this could have happened in a precise place and time (Gremillion et al. 2014). The suggested explanations are a mix of natural (environmental) factors affecting evolutionary behavior and adaptation to new environments, or even the creative nature of human minds, able to learn from natural process of biological reproduction, interfere with them in an intentionally way and building as a result a new artificial environment.

This is the obvious domain for computer simulations. Can agriculture and related practices of animal control emerge "mechanically" in a group of agents originally defined as foragers and predators? The technological side of this transition is not the result of the "intelligence" of some individuals who "invented" something new. As computational simulations have proved (Cribb 1987; Grosman 2005; Ch'ng and Stone 2006; Conolly et al. 2007; Pearsall 2007; Allaby et al. 2010, 2015; Schreinemachers et al. 2011; Fuller et al. 2012; Gerbault et al. 2014; Larson and Burger 2013; Smith 2015a, b; Perrot et al. 2016; van Vliet et al. 2016), domestication of plants and animals is an evolutionary emergent result. Therefore it seems that there are some possibilities that one of the most relevant transitions in the history of humanity had also a mechanical basis.

The following case studies are a good example of the way early agriculture can be simulated computationally. Lancelotti et al. (2014) have created a simple Agent Based Model in which agents relied on a pure subsistence strategy based on domesticated plants and animals. The model explores the role of climate, agricultural production and surplus, and animal availability on the resilience of agro-pastoralists communities on a simplified version of a semi-arid environment. The world where the agents move is divided in three randomly distributed types (dune, interdune and water). The environment state is tracked by the entity World, which takes care of generating the rain, updating the biomass quantity of the cells (depending on their state and type). Interdune type cells can be in one of three states: wild, crop and fallow. The agents derive their caloric intake form crop cells. The relationship rain-biomass-crop-calories is derived by ethnographic and ecological sources and it is based on species of small-millets. The data considered regard rain-fed, manual agriculture, which is believed to be the closest to incipient cultivation system. The agent is modelled as a couple with possible offsprings and the demography tracked yearly, based on the number of days in the year when the agent does not meet her caloric needs (starvation rate). Agent behaviour is focused on resource management. For this reason the model is based on 3 types of actions: (1) searching a suitable place where to settle (which allows both sedentary and some forms of spatial-residential mobility; (2) managing farm activities: harvest the calories from the plots by transforming wild cells in crop once the agents select them as their potential plot; (3) managing animals: in those cases when the agents do not meet their caloric intake with the crops they can use the calories provided by the meat of the animals in their herd.

Barton (2014) has simulated prehistoric swidden cultivation. The model can be run in controlled and adaptive modes. In the controlled mode, the researcher controls all the parameters that govern land-use, and sets them prior to running the model. These land-use parameters include: (1) the initial number of households that start a simulation, (2) the minimum amount of accumulated resources for a household to fission and form a new household, (3) the maximum distance farmers travel to cultivate fields, and (4) the level of low resource returns at which a household will decide to abandon a farm and move to a new locale. All households begin with an arbitrary 100 energy units. These energy units serve as the currency for land use costs, returns, and decisions. The researcher also controls a number of environmental parameters, including: (1) harvest return, (2) costs to clear land, and (3) costs to farm—all expressed as percentages of the initial energy units—along with (4) the rate at which fertility is lost when a parcel of land is farmed, and (5) is regained by soil when a patch is left fallow (in energy percentage lost/gained per time unit). A percentage of bad years can be set during which harvests are only half the normal. Finally, there are settings for land ownership and an adaptive mode that will be discussed below. The landscape of the virtual world that farming households inhabit is initially covered completely by woodland. Households select land parcels that they clear of vegetation to farm. Each modeling cycle, each household selects a parcel to cultivate within the radius of the maximum distance it will travel to farm. Land is selected so as to maximize farming returns and minimize the labor costs of land clearance and walking from farmstead to field. Land farmed in a previous cycle needs less labor for clearing, but will produce lower returns because fertility declines the more it is cultivated. If a parcel is left fallow, it begins to regrow vegetation and can return to woodland after 50 modeling cycles. Fallowed land may also regain fertility if the researcher has set a non-zero rate for soil rejuvenation.

Aagesen and Dragićević (2014) have developed a model to examine the spatio-temporal land-use changes and population responses of early agricultural communities under a variety of environmental and cultural conditions. Complex systems theory and geographical information systems (GIS) are integrated into the design of the model. The resulting Early Agricultural Resources and Land-use Investigation (EARLI) model couples agent-based modeling (ABM) and cellular automata (CA) techniques within a GIS framework. The model examines how both cultural and environmental factors influence land use change under multiple scenarios.

A naturalistic explanation of the origins of plant domestication and agriculture, not making any reference to human motivations nor intentions has been presented by Lemmen and colleagues (Lemmen and Wirtz 2006; Lemmen et al. 2011a, b, 2015; Lemmen 2012, 2015a, b). GLUES, a computer program simulating human population density, technological change and agricultural activity directly, based on the concept of gradient adaptive dynamics, where adoption of a subsistence lifestyle, e.g., Neolithic agriculture, by any given group of people at any particular time depends on endogenous environmental and social factors, e.g., potential productivity, population density, and exogenous factors, including the presence of farming people in neighbouring regions. Simple rules in GLUES, including continent size and climate, allow the model to simulate the spontaneous transition to farming in certain regions of the world. Once farming is established, the model simulates the advection of peoples and diffusion of ideas and technology across environmental gradients. The model is driven by static maps of potential productivity and climate on regions of ca. 1000 km^2 that are defined as areas of relatively homogeneous climate and productivity. GLUES can further use information on climate variability prescribed as discrete events in space and time to influence human activities and populations. GLUES' prognostic outputs include population density, relative proportions of farming people in the region, and the level of technology used by the farming people. The major disadvantage of this computer simulation of the origins of agriculture is that it may produce histories of society-environment interactions that are at-odds with reality, e.g., the spontaneous development of agriculture in places where it is not known to have occurred. Saqalli and Baum (Chap. 8) offer a deep examination of GLUES and related explanatory models of agriculture origins.

If Lemmen's model does not take into account human rationality in the origin of agriculture, Tisdell and Svizzero (2016) and Sterelny (2015) have explore more behavioral approaches, such as satisficing types of behavior. Particular attention is given to social embedding as a constraint on economic change and to non-marginal limitations to economic evolution. The authors assume rational optimizing, and argue that satisficing theories provide a superior explanation of transition (and non-transition) by some hunter-gatherers. They conclude that many of the concepts associated with neoclassical economics are shown to be inadequate for analyzing the choice problems involved. Behavioral models take into account the relationship between human behavior and economic evolution paying attention to the way that decision-making is embedded in social structures.

There is a lot of interest modeling the transition towards agriculture as a wave of advance generated by the spatio-temporal spread of a new population (see Fort et al., Chap. 5). Based on the pioneering work by Cavalli-Sforza and Ammermann (1979), Cohen (1992), Ackland et al. (2007, 2014), Cohen and Ackland (2012a, b) has developed the original model based on fundamental concepts of food production, birth and death rates for various cultures. He and his collaborators showed how some cultures could expand at the expense of others. In the case of Neolithic farming, the form of the equation is similar to Fisher's, but since it was derived rather than postulated, it was also possible to deduce more subtle features. In particular, the equations only allow for a wave of advance of farming if the farmers have a birthrate higher than that of the Mesolithic hunters and gatherers they are displacing or absorbing. This may be due to their more sedentary lifestyle making childcare easier, a hypothesis which is borne out by observation in contemporary farming and nomadic societies. More unexpectedly, the model required that farmers should be less well-nourished and have shorter lifespans than the hunter gatherers they displaced, showing that the strategy more successful for advancing the culture may not be better for the individuals practicing it.

Parisi et al. (2003), Cecconi et al. (2006) follow a different approach within the same problem using cellular automata, which can be seen as a simplified version of an agent-based model. They have simulated the agricultural colonization of Europe from the VII to the IV millennium BC, and its possible similarity with the prehistoric differentiation of European languages. A similar simulation has been developed by Drechsler and Tiede (2007) in the case of the spread of Neolithic herders within the Near East, towards the Arabian Peninsula. In the model, environmental local features influence a global innovation diffusion pattern. Here, computational agents represent mobile populations. The spreading process itself is simulated by a repeated generation of random agents in space. The random component represents the archaeology incomprehensible decisions that lead to human displacements. Because it is more likely that "wandering groups" populate nearby places than faraway places, the possibility for the adoption on an innovation like agriculture is highest in the direct neighborhood of prior acceptance of innovation. Therefore, the random agents cluster spatially more frequently around the "parent" nodes. The spreading surface represents a combination of environmental parameters that are considered fundamental to the dispersal of Neolithic herders across the Arabian Peninsula. These parameters were evaluated for their influence on the movement of human groups, reclassified, and combined to obtain a spreading surface that represents local resistance to the process of spreading. As a result:

- Every place in each generation decreases the underlying raster value simulating the drain on resources and its exploitation value.
- The number of descendants at each place in each generation depends on the value of the underlying raster. The higher the value ("better conditions"), the greater will be the number of descendants in the next generation.
- The actual spreading distance ("how far a new generation will go") also depends on the underlying raster value. The lower the raster value at a specific point, the higher the spreading distance.

The origin of agriculture and production economies as a consequence of the combination of demic processes and cultural transmission mechanisms is now a relatively popular subject of research. Joaquim Fort and Neus Isern have published extensively on this point (Fort 2011, 2012, 2015; Fort and Méndez 1999; Isern and Fort 2008, 2010, 2012; Isern et al. 2012). Fort et al. (Chap. 5) suggest a combination of demic processes of population substitution and cultural transmission, that is, the spread of ideas (hunter-gatherers becoming farmers) instead of populations. They consider an abstract population of preindustrial farmers, initially located in some region, and assume they can disperse into other regions that are also suitable for farming but initially empty of farmers. The idea is that the next generations of farmers will disperse away from their parents and agriculture will propagate to neighbor areas as a wave of advance. The authors modify the classical Fisher's reactive model to predict the specific dynamics of such a wave of advance, taking also into consideration an integro-difference cohabitation model between newcomers (farmers) and indigenous populations (hunter-gatherers) in which cultural transmission from farmers to hunter-gatherers leads to a more complicated model.

Other relevant work exploring many alternative hypothesis on the causes of human movement and the spread of innovation with such historic contexts have been published by Barbujani et al. (1995), Di Piazza and Pearthree (1999), Excoffier et al. (2008), Cabana et al. (2008), Connolly et al. (2008), Boquet-Appel et al. (2009), Barton et al. (2010a, b), Baggaley et al. (2012), Hervella et al. (2012), Rasteiro et al. (2012), Currat and Silva (2013), Düring (2013), Gerbault et al. (2013), Ullah (2013), Guedes et al. (2014), Le Néchet et al. (2015), Silva and Steele (2015), Bernabeu et al. (2015), Gordó et al. (2015).

Sakahira and Terano (Chap. 10) also deal with a similar issue. These authors analyze the arrival of Chinese-Korean immigrants during the establishment of the agrarian culture of the Yayoi period (300 BC–250 AD) in Japan. The agrarian culture is reported to have been imported from China-Korea. Thus, the presence of Chinese-Korean immigrants was evidently of importance during the establishment of the Yayoi culture when agriculture became the social and economic foundation of society. However, several factors pertaining to these immigrants remain unclear within Japanese anthropology and archaeology. Specifically, these relate to the immigrants' place of origin, the initial immigrant population size, the sex ratio of the immigrants, and whether native hunter-gatherer people or farmer immigrants played a formative role in the establishment of agrarian culture during the Yayoi period. This contribution focus on two issues: (1) the sex ratio of the immigrants, and (2) the question of who played a formative role in the development of the agrarian culture during the Yayoi period. This simulation model demonstrates that in the event that most of the initial immigrants were male, and that an agrarian culture was widely adopted by native hunter-gatherers people during the early stage of its development, it is probable that after 300 years, the majority of people shared the same traits as the immigrants. The authors have simulated three possible scenarios. In the first, immigrants were polygamous and the agrarian culture was only inherited from a parent agent (not diffused from neighboring agents). In this case, the descendants of agriculturalists at an early stage were either immigrants or both immigrants and native hunter-gatherers people. Thus, immigrants played a formative role in the establishment of an agrarian culture. In the second case, immigrants were polygamous and the agrarian culture was inherited from a parent agent as well as diffused from neighboring agents. However, the diffusion of the agrarian culture occurred slowly. In this case, the descendants of the agriculturalists at an early stage were mostly immigrants with few native hunter-gatherer people. As in the first case, immigrants played a formative role in the establishment of an agrarian culture. In the last case, the diffusion of the agrarian culture was significantly more rapid. In this case, the majority of descendants of agriculturalists were immigrants at the earliest stage, but shortly thereafter, native hunter-gatherer descendants were evident during a subsequent early stage. Here, mostly Jomon people and a few immigrants played a formative role in the establishment of an agrarian culture. Of these three probable cases, the last is the most consistent with anthropological and archaeological evidence for the following reasons. In the first case, the diffusion rate of agriculture was too low.

Matsumoto and Sasakura (Chap. 11) develop the same case study as Sakahira and Terano (Chap. 10), that is, hunter-gatherer to farmer transitions in Japan as a consequence of the arrival of new populations with a new economy and the hybridizing with local populations. Drastic socio-cultural changes in subsistence, material culture and settlement structure occurred in the northern part of Kyushu Island around 10th–8th centuries BC., and they seem related with the arrival of new populations, and the consequent pattern of interaction between populations and cultural transmission between newcomers and local settlers, which ended with the acculturation of indigenous populations. The authors consider that decisions concerning cultural integration, transformation and adoption/rejection of cultural elements were important factors in this transition, but they only focus on cultural transmission aspects for the sake of simplicity. A simulation of 500 years of accumulated changes shows that cultural skill could have spread quickly without much loss in the case of biased transmission, even in case the migration rate was very low, and that the spread of cultural skill without significant genetic influence was possible even when cultural transmission was restricted to between relatives. The result gives an inspiration for possible explanatory models of hunter-gatherer/farming transition in Japan in which indigenous people play more significant roles in areas remote from the locus of Yayoi cultural origin. Among their main results, we can quote:

- The rate of population increase can considerably vary due to chance factors, while the spread of genetic value is almost constant as the same marriage rules and move rate were applied to all runs.
- Cultural skill can spread quickly without much loss in the case of biased transmission, even when migration rate is maintained very low.
- The spread of cultural skill without significant genetic influence is possible even when cultural transmission is restricted within relatives.
- Nonrandom migration based on family relationship may facilitate the spread of g-value.

These models of social transition built on the assumption of population spread rely on complex mechanisms of population growth. Important work has been done on this aspect, trying to model the mechanisms of social reproduction, fertility, marriage and mortality in small-scale early agricultural societies (Artzrouni and Komlos 1985; Komlos and Nefedov 2002; Low et al. 2002; Jager and Janssen 2003; Fletcher et al. 2011; Baggaley et al. 2012; Machálek et al. 2012; Rasteiro et al. 2012; Rogers et al. 2012; Geard et al. 2013; Séguy and Buchet 2013; Lemmen 2014; Puleston et al. 2014; Diachenko and Zubrow 2015; Shennan 2015; Sajjad et al. 2016; Winterhalder et al. 2015). As an example of these kind of investigations we can quote Iwamura et al. (2014), who have developed a holistic model framework with agent-based modeling to examine interactions between demographic growth, hunting, subsistence agriculture, land cover change, and animal population in a particular geographical area, investigating the conditions under which indigenous communities relying on hunting and subsistence agriculture alter their impacts on an ecological system through land use change. This is a spatially-explicit household simulation mode, and it is meant to analyze the feedback between human activities and natural resource systems. The authors use an extensive field dataset from social surveys, animal observation records and hunting kill locations along with satellite images. The model exhibits feedback loops between a growing human population and depletion of local natural resources. The model can reproduce the population size of two different villages along with landscape patterns without further calibration. This model has been used for understanding the conditions of sustainability for indigenous communities relying on subsistence agriculture and hunting, and for scenario analyses to examine the implications of external interventions.

In the same way as Chaps. 3 and 4 tried to reproduce in silico hunting and gathering ways of living in prehistory, we can reproduce computationally the social life of first farmers. Figueiredo and Velho (2001) have programmed a system based on three different kinds of agents: cattle, hunters, and farmers. These agents compete for natural resources (plants). The success of each type of agent is determined not only by the availability of the natural resource but also by the capability of other agents to gather those resources for themselves. Running the model consists of creating a landscape and introducing initial populations of animal and hunters. The initial group of hunters follows the cattle around killing them whenever possible. The killing rule relates the energy of the animal to the number of humans in cells around it. So the kills are determined by the patterns of movements of animals and hunters. As the animals follow the concentration of plants, and hunters the concentration of animals, the two groups move close together. Farming disturbs the natural availability of resources. Farmers are located in the same locations were animals eat. Cattle are competitors for farmers, hunters are competitors for hunters, farming increase the number of cattle. Vaart et al. (2006) used a similar approach to understand the consequences of the different social mechanisms related to the management of wild preys and domesticated cereals. Saqalli et al. (2014) describe another spatialized Agent-Based model, reconstructing the society system of the oldest central European farming communities (Linear Band Keramik, circa 5500–4500 BC) functioning at the village level. The idea was to reconstruct in the same model the functioning along a local grid level (1 ha/cell) of village societies. The goal of this combination of scale was that small variations at the farming/livestock keeping/hunting-gathering system do have exponential effects on a larger scale.

Saqalli and Baum (Chap. 8) discuss different "Terroir"-based environmentally constrained models based on information from local archaeological data regarding environmental characteristics (soil, vegetation, local climate, distance to village) and cropping and livestock-keeping practices, to evaluate the environmental impact of human settlements over several village territories, along several farming scenarios (shifting, intensive garden and non-intensive cultivation) and diet assumptions.

Tilman Baum (Chap. 9, see also Baum 2014) analyses some aspects of the economic and social life of first farmers in Europe. He presents WELASSIMO, an Agent-Based Model simulating land use of Neolithic wetland settlements in the Swiss and German pre-alpine forelands. Its aims are to test whether any of the existing hypotheses would justify a settlement relocation for systemic reasons. It is shown that for relatively small communities, the non-finite resources related to their land-use most likely have not been limiting and thus did not determine the observed settlement pattern. Instead, it is argued that the continuous duration of moderate land-use did increase the economic value of the evolving landscape. Thus, it is proposed, that relocations happened mostly inside of the relevant landscapes as a combined consequence of the poor durability of wooden houses in waterlogged environs and the spatiotemporal variability of suitable timber. This does not exclude the possibility, that also cultural/social reasons may have been involved. The aim of WELASSIMO to fill this gap and, more specifically, to answer the following questions:

- What implications and systemic feedbacks go alongside with the published hypotheses on land-use systems?
- What was the spatial and temporal availability of non-finite resources?
- Can excessive resource use have caused the observed dynamic settlement pattern?

Within the research domain of agricultural societies, the VIRTUAL ANASAZI project (Dean et al. 2000; Axtell et al. 2002) is another example of agent-based modeling designed to investigate where early agricultural prehistoric communities of the American Southwest would have situated their households based on both the natural and social environments in which they lived. The idea was to define nuclear families (households, the smallest social unit consistently definable in the archaeological record) as agents, and loosed them on landscapes, which have been archaeologically studied for different historical periods, and plenty of paleo-productivity data exist. The model has been used to predict individual household responses to changes in agricultural productivity in annual increments based on reconstructions of yearly climatic conditions, as well as long-term hydrologic trends, cycles of erosion and deposition, and demographic change. The performance of the model is evaluated against archaeological data of population, settlement, and organizational parameters. By manipulating numbers and attributes of households, climate patterns, and other environmental variables, it is possible to evaluate the roles of these factors in prehistoric culture change. Here the household is a theoretical construct, but it moves on a historically defined environment, which is the most precise available archaeological data allow. Simulated population levels closely follow the historical trajectory. In the first 200 years, the model understates the historical population, whereas the peak population just after A.D. 1100 is somewhat too high in the model. The historical clustering of settlements along the valley zonal boundaries is nicely reproduced. Although the ability of the model to predict the actual location of settlements varies from year to year, the progressive movement of the population northward over time, clear in the historical data, is also reproduced in the simulation. Long House Valley was abandoned after A.D. 1300. The agent model suggests that even the degraded environment between 1270 and 1450 could have supported a reduced but substantial population in small settlements dispersed across suitable farming habitats located primarily in areas of high potential crop production in the northern part of the valley. The fact that in the real world of Long House Valley, the supportable population chose not to stay behind but to participate in the exodus from the valley indicates the magnitude of socio-cultural "push" or "pull" factors that induced them to move. Thus, comparing the model results with the actual history helps differentiate external (environmental) from internal (social) determinants of cultural dynamics. It also provides a clue—in the form of the population that could have stayed but elected to go—to the relative magnitude of those determinants.

Ultimately, “to explain” the settlement and farming dynamics of Anasazi society in Long House Valley is to identify rules of agent behavior that account for those dynamics (Dean et al. 2000). To “explain” an observed spatiotemporal history is to specify agents that generate—or grow—this history. By this criterion, this strictly environmental account of the evolution of this society during this period goes a long way toward explaining this history (Axtell et al. 2002). The simulation imitates the target data by computing the individual agents’ behavior in response to some input environmental data, by computing the effects of the individual behaviors on the environment, and by computing the repercussions these environmental effects have on individual agents. As shown, this ‘best fit’ still does not necessarily accurately replicate the historical findings. In particular, it simulates a higher population early on, and does not replicate the complete eclipse of the settlement in around 1300. The authors point out that better fits can be achieved by increasing the number of household attributes and their heterogeneity, possibly introducing non-uniform distributions.

The evolution of the Virtual Anasazi project can be seen in the similar but at a much higher scale “Village Ecodynamics” project by Kohler and his colleagues (Kohler 2003, 2013; Kohler and Carr 1997; Kohler and Yap 2003; Kohler et al. 2000, 2005, 2007; Kohler et al. 2012; Kohler and Varien 2012; Johnson et al. 2005; Crabtree 2015). Some interesting details of this model are also discussed in Saqalli and Baum contribution to this volume (Chap. 8), Kohler and associates began by entering paleo environmental data on a digitized map of the area, and then placed the agents—simulated households—randomly on the map. The primary area of research is the study of the effect of exchange relationships upon the formation of larger social groups. Since agricultural yields varied greatly from year to year, farmers needed to adapt mechanisms to reduce their uncertainty of future yields. One such mechanism thought to be important is reciprocity between households. After a reasonable model of agent planting was constructed, agents were endowed with balanced reciprocity behaviors and adaptive encodings of exchange, placing the households into a social and an economic network or other (related and unrelated) households. This network is flexible enough to evolve according to agent interactions and changes in the world environment. The authors are also trying to include the natural production and human degradation of what they consider Critical Natural Resources into the agent-based simulation modeling of household settlement patterns. By demonstrating the ease with which populations could have depleted fuels in this environment, for instance, the simulation builds a context in which changes in food preparation, craft production, architecture, frequency of axes, and so forth, which might be responsive to fuel scarcity, become more plausibly interpreted as having been intended to do so (Johnson et al. 2005).

In recent simulations, the authors have extend the previous model by adding the ability of agents to perform symmetrically initiated or asymmetrically initiated generalized reciprocal exchange (Reynolds et al. 2004a, b, 2005a, b; Kobti and Reynolds 2005). According to this model, the decision made by the group is a not consensus based upon the weights and opinions of the members, but the individual knowledge is pooled and used by a central decision maker to produce a decision (Reynolds and Peng 2005). Selected individuals contribute to the cultural knowledge, which is stored and manipulated based on individual experiences and their successes or failures.

A small world social network emerged and the resultant agent populations were shown to be more resilient to environmental perturbations. When allowing agents more opportunities to exchange resources, the simulation produced more complex network structures, larger populations, and more resilient systems. Furthermore, allowing the agents to buffer their requests by using a finite state model improved the relative resilience of these larger systems. Introducing reciprocity that can be triggered by both requestors and donors produced the largest number of successful donations. This represents the synergy produced by using the information from two complementary situations within the network. Thus, the network has more information with which it can work and tended to be more resilient than otherwise (Crabtree 2015).

Cockburn et al. (2013), Crabtree (2015) have developed the original model by introducing a new model for agent specialization in small-scale human societies that incorporates planning based on social influence and economic state. Agents allocate their time among available tasks based on exchange, demand, competition from other agents, family needs, and previous experiences. Agents exchange and request goods using barter, balanced reciprocal exchange, and generalized reciprocal exchange. The authors use a weight-based reinforcement model for the allocation of resources among tasks. In the base model, agents represent households seeking to minimize their caloric costs for obtaining enough calories, protein, fuel, and water from a landscape which is always changing due to both exogenous factors (climate) and human resource use. Compared to the baseline condition of no specialization, specialization in conjunction with barter increases population wealth, global population size, and degree of aggregation. Differences between scenarios for specialization in which agents use only a weight-based model for time allocation among tasks, and one in which they also consider social influence, are more subtle. The networks generated by barter in the latter scenario exhibit higher clustering coefficients, suggesting that social influence allows a few agents to assume particularly influential roles in the global exchange network.

The Virtual Anasazi and the Village Ecodynamics models are among the most influential computer simulations of prehistoric societies. This impact is easily observed in modern publications that model different aspects of social life in early agrarian societies (MacMillan and Huang 2008; Gabler 2012; Barton et al. 2014).

SimpopLocal is a stylized model describing an agrarian society in the Neolithic period, during the primary "urban transition" manifested by the appearance of the first cities (Schmitt et al. 2015). It is designed to study the emergence of a structured and hierarchical urban settlement system by simulating the growth dynamics of a system of settlements whose development remains hampered by strong environmental constraints. This exploratory model seeks to reproduce a particular structure of the Rank-Size distribution of settlements well defined in the literature as a generalized stylized-fact: for any given settlement system throughout the time and continents, the distribution of sizes is strongly differentiated, exhibiting a very large number of small settlements and a much smaller number of large settlements.

Ortega et al. (2014, 2016) examines an alternative approach to previously proposed models of prehistoric exchange to explain the distribution of obsidian across the Near East during the Neolithic period. Obsidian exchange is a complex system where multiple factors interact and evolve in time and space. Through Agent-Based Modelling simulations of an hypothetical exchange network where some agents (villages) are allowed to attain long-distance exchange partners through correlated random walks, the authors suggest that when additional variables (population density, degree of collaboration between villages…), a type of small-world exchange network could explain the breadth of obsidian distribution (up to 800 km from source) during the Near Eastern Neolithic.

In the same line, Cleuziou (2009) suggests modeling social evolution in conjunction with environmental changes by using non-linear multi-agent models is a much more fruitful way to understand the shift from coastal to inner environments by mid-3rd millennium BC and the apparent depopulation of the Oman Peninsula by 2000 BC. Rouse and Weeks (2011) have recently investigated the role of specialized production strategies in the development of socio-economic inequalities in Bronze Age south-eastern (SE) Arabia, and particularly, the ways in which a localized, internal exchange economy may have produced stress and instability in the SE Arabian socio-economic system. The agent-based model the authors have built with that perspective suggests the nature of the internal exchange economy in SE Arabia itself may have precipitated the social conditions necessary for change by allowing individuals to profit disproportionately.

In the Bronze/Iron Age, approximately 1500/500 years before our era, most human societies adopted production economies in the Old World, and some early forms of social complexity began to develop. Widgren (1979) was one of the very first researchers in modeling how those ancient economic systems worked. Kowarik et al. (2012, 2015) have modelled social life and ancient production techniques of the Bronze Age salt mining complex of Hallstatt/Austria (1458–1245 BC). The authors have addressed the complexity of production structures and especially their interaction with the natural and socioeconomic surroundings: what were the demands concerning workforce, means of production and subsistence? How many people had to be supplied with means of production and subsistence? Were the local resources sufficient? The authors have used Agent-Based Simulation to build a model of the working processes in one mining hall (breaking salt, collecting salt, transporting salt to the shaft), in order to gain insights into spatial organization, allocation of tasks and workload balance and to relate the time span of mining to the size of the workforce and the amount of mined salt. A System Dynamics Simulation was applied to correlate the size of the workforce (population dynamics) with food consumption and demand for mining tools. Through Process Simulation, the authors were able to display and analyze the workflow of an entire shaft system encompassing several mining halls.

Štekerová and Danielisová contribution to this book (Chap. 12) can also be regarded as an example of simulating farming economic systems before the full consolidation of social complexity. Authors approach computer modelling as a tool for understanding Celtic society and cultural changes at the end of the East European Iron Age. They focus on development of agent-based models of daily economic activities of inhabitants of Late Iron Age agglomerations (oppida), aiming to verify hypotheses about the probable self-subsistence of oppida by means of models of the population dynamics and socio-economic behavior of one particular site, the Staré Hradisko oppidum in Bohemia. The core concept is the idea of society pursuing agro-pastoral activities within the given temporal and spatial scale which is tested against subsistence, surplus production and carrying capacity factors. They aim to explore the dynamics of the food production and isolate possible crisis factors imposed either by environment or by unsustainability of the economic strategies pursued. Main questions throughout the chapter are:

- What is the maximum population that can be sustained in a given environment and when is this maximum reached?
- Using what cultivation strategies and labor input can the population most effectively exploit natural resources in order to be self-sufficient?
- What are the dynamics of production with constantly growing or declining population (subsistence–surplus–success rate–diminishing returns)?

In Štekerová and Danielisová's model, the whole Iron Age world despite its technological innovations, specialization and economic contacts, or its level of complexity, was still principally a world of the common farmer. It appears as part of a socio-economically advanced environment, together with a distinctive intensification of settlement patterns. Central places are programmed in historically reliable environments as "total consumers". That generally means that they were too specialized and hence engaged in other activities, so they were not capable of producing any foodstuffs. This fact should have eventually contributed decisively to the collapse of the Iron Age society in the 1st century BC. Some of these settlements surely had to overcome or accept some environmental constrains (imposed for example by higher altitude) or were forced to adapt their subsistence practices (e.g., develop an alternative approach to the exploitation of land). To answer these questions, they developed three models: the population dynamics model, subsequent food production and land use model and workforce allocation model. The model of population dynamics generates data on synthetic population for four alternative depopulation scenarios, the model of food production and land use is designed to enable experimenting with carrying capacity of the environment with respect to alternative exploitation scenarios, and finally, the work-force model is used for studying allocation of working capacities during the harvest season which is understood to be one of "bottlenecks" of the agricultural year. The aim is especially to ascertain the resilience of the food production system (i.e., carrying capacity) of the oppida under the dynamically changing (increasing/decreasing) population. The models are designed to enable experimenting with alternative scenarios and strategies with the aim to test various upper limits of self-subsistence of the oppidum and to verify general theoretical hypotheses related to the functioning of the oppida within particular landscape environment and the ecological and economic rules that were shaping them.

The same authors have also explored related subjects, like the effects of population growth (Olševičová-Štekerová et al. 2013), and the configuration of a settlement network (Olševičová-Štekerová et al. 2015; Danielisová et al. 2015).

The work by Kim (2015) on the simulation of Bronze Age Korea can also be related with the economic and political evolution of prehistoric agricultural societies. The author argues that sociopolitical development in the central and southern parts of the Korean Peninsula during the Early Bronze Age–Middle Bronze Age transition might have been closely related to economic intensification. This can be understood from a perspective that emphasizes elite control over basic economic resources as a significant factor in this development.

1.2.7 Why Humans Have Made Life Even More Complex and Difficult. The Making of the State and the Origins of Class Struggle

The economic change implied in the transition from predator and forager based survival to full productive economies based on agriculture, herding and stock-breeding subsistence settled the basis for a new social organization and new forms of political decision making. Computer modeling allows researchers to understand major transitions as involving several interacting processes: evolution of cooperation among lower-level units, selection which acts on higher-level “collectives,” policing mechanisms which suppress “free riders” and competition among lower-level units, and increased functional integration of collectives which makes them increasingly organism-like (Turchin 2013). Eventually, higher-level collectives become so well integrated that they can be treated as “individuals” in their own right (and can serve as lower-level units for the next evolutionary transition).

Different authors have generated computer simulations to understand how hierarchical decision-making could have affected inter-group conflicts sometime through the historical evolution of human society (Mark 1998; Suleiman and Fischer 2000), the dynamics of status symbols in hierarchically ordered societies (Pedone and Conte 2001), the consequences of wealth distribution (Impullitti and Rebmann 2002), the coevolution of farming and private property (Bowles and Choi 2013; Bowles et al. 2010; Cockburn et al. 2013; Angourakis et al. 2015; Biscione et al. 2015; Gallagher et al. 2015), the deification of historical figures and the emergence of priesthoods (Dávid-Barrett and Carney 2015), the origins of war (Duering and Wahl 2014) and the Neolithic transition from egalitarianism to leadership and despotism (Levine and Modica 2013; Powers and Lehman 2015). Those models and simulations explain how, despite being an unlikely event, farming and a new system of property rights jointly emerged when they did, as an emergent property of the new possibilities of unambiguously demarcate and defend the new wealth produced and stored by farmers—crops, dwellings, and animals—. Farming and private property may have spread as a result of adoption by most individuals in a group occurring either as the result of changes within the group or from emulation by a group of foragers and their subsequent adoption of the new institutions and technology.

Computer simulations results thus challenge unicausal models of historical dynamics supposedly driven by advances in technology, population pressure, adaptation to climatic change or other exogenous influences (Pujol et al. 2005). Especially important to understand the development of means of production and the consequent emergence of new relations of production is the possibility to simulate computationally the emergence of specialization, in which different individual agents spontaneously assuming different roles in the execution of the task (Parisi and Nolfi 2005). The most effective strategy includes primitive forms of "situated" specialization in which identical individuals play different roles according to the circumstances such as leading or following the group. These forms of functional specialization seem to be due to the need to reduce interference between potentially conflicting sub-goals such as moving toward the rest of the group to maintain aggregation and moving toward the target. Imagine a group of agents that has to reach a target in the environment but to be rewarded they must approach the target by maintaining reciprocal proximity. If the agents are initially dispersed in the environment, they may be unable to perceive each other and therefore they may be unable to aggregate and then move together toward the target. The solution is to evolve some signaling behavior that allows the group to aggregate. On this question, Cokburn et al. (2013) add the effect of social influence to increase the level of specialization. Building on these assumption, these authors have created a model that incorporates both economic state and social influence. Agents are influenced by competition from other agents in their topographically based social network. It is expected that there should be more task specialization in this socially influenced system than in the models without social influence. Further, specialization and social influence may have effects on populations of agents, and as social influence interacts with exchange networks, it is expected that specialization may introduce changes in the structure of global populations.

To sum up, it is the mechanism of change itself which produces the emergence of new social configurations. This idea is basic to understand the evolution from prehistoric small-scale societies to historical complex polities. This has been a traditional topic for archaeologists, anthropologists, historians and social and political theorists (Lull and Micó 2011), and we can read more different theories than theoreticians have thought thereof. Fortunately for us, Henri Francfort has shown how 2000 years of historical narratives can be easily resumed in a few hundred lines of computer code (Francfort et al. 1989; Francfort 1997). In any case, politogenesis should be never reduced to the only one evolutionary pathway leading to the statehood (Grinin 2009). The early state formation was only one of many versions of development of complex late archaic social systems. The state is nothing more than one of many forms of the post-primitive socio-political organization; these forms are alternative to each other and are able in certain conditions to transform to one another without any loss in the general level of complexity.

Foundational work on the idea to simulate the historical processes towards the origin of state societies and complex polities was Epstein and Axtell's Sugarscape model. It simulates the behavior of artificial people (agents) located on a landscape of a generalized resource (sugar). Agents are born onto the Sugarscape with a vision, a metabolism, a speed, and other genetic attributes. Their movement is governed by a simple local rule: "look around as far as you can; find the spot with the most sugar; go there and eat the sugar." Every time an agent moves, it burns sugar at an amount equal to its metabolic rate. Agents die if and when they burn up all their sugar. A remarkable range of social phenomena emerge. For example, when seasons are introduced, migration and hibernation can be observed. Agents are accumulating sugar at all times, so there is always a distribution of wealth. Based on this simplified scenario, Epstein and Axtell attempted to grow a metaphoric "proto-history" of civilization. It starts with agents scattered about a twin-peaked landscape; over time, there is self-organization into spatially segregated and culturally distinct "tribes" centered on the peaks of the Sugarscape. Population growth forces each tribe to disperse into the sugar lowlands between the mountains. There, the two tribes interact, engaging in combat and competing for cultural dominance, to produce complex social histories with violent expansionist phases, peaceful periods, and so on. The proto-history combines a number of ingredients, each of which generates insights of its own. One of these ingredients is sexual reproduction. In some runs, the population becomes thin, birth rates fall, and the population can crash. Alternatively, the agents may over-populate their environment, driving it into ecological collapse. When Epstein and Axtell introduce a second resource (spice) to the Sugarscape and allow the agents to trade, an economic market emerges. The introduction of pollution resulting from resource-mining permits the study of economic markets in the presence of environmental factors (Epstein and Axtell 1996).

This computing example shows how complexity unconsciously emerges as a side effect of individual decisions (Mark 1998). Here complexity refers to diversified patterns of social organization and political institutions controlling, constraining and determining social behavior. The original Sugarscape model has been updated and modified many times (Costopoulos 2015). The Virtual Anasazi project, as reviewed in the preceding section, was a direct consequence of Epstein work, addressed to the empirical testing of the social principles behind the model (Swedlund et al. 2015). Flentge et al. (2001) have extended the sugarscape model giving the agents the possibility to claim possession of a "plot" of land. Memes regulate the behavior of the agents regarding the land claims of others. It turns out that the probability for the survival of the population is much higher when possession claims of others are respected. However, there exist short term disadvantages for agents respecting the possessions of others. Thus, the need for a possession norm arises. The introduction of sanctions provides a good possibility to enforce the norm as long as no costs arise for sanctioning agents. Rahman et al.

(2009), have added social classes (poor, mid, and rich) and have studied the consequences of wealth distribution among all agents. Bruno (2011) has explored the economic properties of trade networks emerging from agents' interaction. Pan (2011) has studied the emergence of solution of violence in a sugarscape-derived artificial society using Greed and Grievance Theory of Civil Conflicts. Elsenbroich and Gilbert (2014) consider the influence of environmental factors on social norms; using the sugarscape scenario of a scarce resource environment, the emergence of a possession norm is explored as is the function of such a norm for society.

Sugarscape derived models are not the only ones to understand the formation of heavily institutionalized groups of people. Some alternative models emphasizes the "benefits" of leadership and the long term consequences of social division of labor in the process towards increasing hierarchy in the political organization. Especially relevant for this purpose are mathematical models showing how wealth accumulation depends on the 'social relation' between two classes: owners or workers. As a result, a society may evolve towards an unequal outcome with few rich and many poor individuals (Roemer 1985; Walby 2007; Chadefaux and Helbing 2010; Russo 2014).

For instance, Powers and Lehman (2014) have modeled the historical coevolution of individual preferences for hierarchy alongside the degree of despotism of leaders, and the dispersal preferences of followers. They show that voluntary leadership without coercion can evolve in small groups, when leaders help to solve coordination problems related to resource production. An example is coordinating construction of an irrigation system. Their model predicts that the transition to larger despotic groups will then occur when: (1) surplus resources lead to demographic expansion of groups, removing the viability of an acephalous niche in the same area and so locking individuals into hierarchy; (2) high dispersal costs limit followers' ability to escape a despot. Jahanbazi et al. (2014) have formally modeled the transition from kinship tribes to nation states. Their agent-based simulation, based on existing observational and analytical studies of pre-contact Pacific Island hunter-gatherer societies, examine how different societies' structures were affected by various characteristics and strategies of their chiefs. The model represents the influence of societies' structure on how agents fulfil their basic needs and the consequences of an agent's action on both short term and long term society's survival. The evolving societal structures of the model have long-term effects on wealth inequality and whether the society grows or collapses. The results encourage the idea that significantly different outcomes in social welfare do not necessarily require massive changes to all the agents, but can be achieved by relatively moderate modifications in social structure and the governance of societies.

The most popular computational theories of the origin of state are those considering the nonlinear effects of violence and warfare on the emergence of complex polities. Most of these models are reexaminations of the classical hypothesis by Carneiro (1970). However, the particular characteristics of computational models have allowed to integrate both extremes of the same continuum: altruism—benefiting fellow group members at a cost to oneself—and conflict hostility toward individuals not of one's own ethnic, racial, or other group—. The idea is that neither violence nor altruism would have been viable singly, but by promoting group conflict, they could have evolved jointly (Bowles 2008, Choi and Bowles 2007).

Spencer (1998) proposed a mathematical model of political growth in chiefdoms (societies with centralized but not internally specialized authority) and states (societies with centralized and also internally specialized authority), based on differential equations. A major conclusion of the exercise is that the emergence of a primary state is likely to be accompanied by a considerable expansion in the political-economic (sustaining) territory of the polity. A related issue is how peoples who successfully resist incorporation can help shape the developmental trajectory of an expanding state. Spencer (2014) proposes a model of the dynamic between an expanding polity and its neighbors suggesting that the effectiveness of incorporation is positively related not simply to the size of the expanding polity, but rather to a positive rate of change in the expanding polity's growth relative to that of resisting polities. Variable relationships of incorporation and resistance will cause the shape of the expanding state's growth trajectory to be not regular and symmetric, but instead asymmetric and non-uniform.

Reynolds and Lazar (2002) added the effects of aggregation to a computer model of territorial expansion. With increased aggregation it was no longer possible for a single individual to monitor the entire aggregation. In order to control thousands of farmers, laborers, and warriors, it was required that many tasks be delegated to administrative, scribal, architectural, craft, and military specialists. This resulted in the formation of the state. In order to produce larger degrees of aggregation the span of leadership needed to be extended. This level of aggregation was achieved by changing the meaning of existing relations, implying that only the immediate offspring of current leaders had the right and duty to lead. This allowed leaders to aggregate wealth and resources over generations and extend alliances over larger numbers of surrounding villages. These changing relationships produced a system in which the actors were relentlessly competing, resulting in periodic outbursts of violence. In this system, the culturally defined goals of a leader were to have as many farmers, craftspeople, and warriors under his control as possible. The two main strategies for reaching those goals were: (1) alliance building-through feasting, gift-giving, and bride exchange; and (2) warfare, mostly at the level of raiding and burning rival villages. The escalating warfare lead to a major shift in emphasis on site location from access to high quality agricultural land to the need for defensible locations. This change supported the shift from a ranked society to a stratified one by restricting the ability of lower ranks to marry with those from upper ones. This over time resulted in two basic strata, the elites and the commoners. The pragmatics behind this shift in the meaning of social relationships was engendered by the need to incorporate other conquered, highly ranked elites into the fold via intermarriage valley wide (Jayyousi and Reynolds 2013).

Griffin and Stanish (2007, 2008), Griffin (2011) have modeled how complex early polities expand in size over time to accommodate population growth. Polities also expand due to fusion with other polities, when adjacent polities came into conflict when no empty land separating them remained for expansion. The net result is consolidation, which can be explained in terms of overt conquest or intimidation, forming alliances, religious legitimization, rewarding loyalty, marriage, etc. Internally there was competition between factions within each polity. It seems reasonable to expect that the larger a polity the greater the number of internal factions and hence the more likely resistance would occur. This relationship can be modeled by assuming that the probability of resistance for any one settlement was constant, so the likelihood of resistance somewhere in a polity increased as the number of its settlements grew. The same effect was achieved in the current model by spatially uniform random occurrences of resistance. Polities came into conflict when a settlement is added and bridges the gap between two or more polities. This corresponds to one or more of these neighboring polities attempting to expand into the buffer zone separating them. The center of the prevailing polity retained its current location and became the center of the newly constituted fused polity. The other competing centers became satellite settlements in the new larger polity. The competition's winner is determined by comparing the effective strengths of two, three or four competing centers with the strongest being the winner. The assumption was that the strength of agrarian polities would have been determined by a combination of center's population size and resources discounted by distance. The simulation of these mechanisms concludes that:

- Population rank-size distribution for an area surrounding a single dominant center will be primate immediately before fission and transition to convex thereafter.
- Strengthening each of four integrative processes by adjusting its associated parameter will decrease the time averaged rank-size convexity for the entire grid.
- Subordinate population centers articulated to a primate center or another subordinate center will be observed within polities.

Gavrilets et al. (2014) have developed a spatially explicit agent-based theoretical model of the emergence of early complex polities via warfare. In this model polities are represented as hierarchically structured networks of villages whose size, power, and complexity change as a result of conquest, secession, internal reorganization (via promotion and linearization), and resource dynamics. A general prediction of our model is continuous stochastic cycling in which the growth of individual polities in size, wealth/power, and complexity is interrupted by their quick collapse. The model dynamics are mostly controlled by two parameters, one of which scales the relative advantage of wealthier polities in between and within-polity conflicts, and the other is the chief's expected time in power. Our results demonstrate that the stability of large and complex polities is strongly promoted if the outcomes of the conflicts are mostly determined by the polities' wealth/power, if there exist well-defined and accepted means of succession, and if control mechanisms are internally specialized. The authors present a dynamic quantitative model exploring the origin and operation of early human complex society, focusing on both the size and complexity of emerging polities as well as their longevity and settlement patterns. They systematically examine the effect of parameters such as system size, the effect of polity power on the probability of winning a conflict, tribute level, variation in productivity between individual villages, span of control, and chief's average time in power. The polities in the model exhibit a strikingly fluid nature resembling so-called "chiefly cycles." Unexpectedly, the largest effect on results is due to just two parameters: the scaling of the polity power to the probability of winning a conflict, and the chief's average time in power.

Rowthorn et al. (2014) have developed the effects of behavioral and populational differences in an artificial society divided into 2 hereditary classes: a warrior elite and a productive class. The model entails that the extra cost warriors must incur to train and equip their children for war determines the relative sizes of both classes and the degree of economic inequality. Higher costs of warrior children imply a greater economic advantage for warriors and a smaller ratio of warriors to producers.

Nevertheless, what characterizes complex polities is not only conflict, authority and coercion, but ultrasociety, the ability of humans to cooperate in large groups of genetically unrelated individuals (Centola et al. 2005; Turchin 2015). Such cooperation can take many forms: volunteering for the army when the country is attacked, willingly paying taxes, voting, helping strangers, refusing to take bribes, etc. In each case, the result of cooperation is production of a public good, while the costs of cooperation are born privately. Sustained cooperation requires a solution to the collective action problem stemming from the tension between the public nature of benefits yielded by cooperation and private costs borne by cooperating agents. Social norms and institutions are among the most important ways of solving this problem. Ultrasocial institutions are institutions that enable cooperation at the level of larger-scale human groups. They are characterized by the tension between benefits they yield at the higher level of social organization and costs borne by lower-level units. Of particular interest are ultrasocial institutions, which play a role in the integration of largest-scale human groups; institutions that enabled the transition from middle-range societies (simple and complex chiefdoms) to archaic urban states and subsequently to large-scale empires and modern nation-states (Turchin 2015).

Strong macrohistorical regularities suggest that the rise of any particular mega-empire was not a random result of a concatenation of unique events; general social mechanisms must have been at work. Building on the ideas of the fourteenth century thinker Khaldun, Turchin (2003, 2009; Turchin and Gavrilets 2009; Turchin et al. 2013) has proposed a "mirror-empire" model as one common route to mega-empire. This model postulates that antagonistic interactions between nomadic pastoralists and settled agriculturalists result in an autocatalytic process, which pressures both nomadic and farming polities to scale up polity size, and thus military power. In many cases, as happened repeatedly in China and Ancient Egypt, the result of this process is the simultaneous rise of an agrarian empire and a nomadic imperial confederation on their respective sides of the steppe frontier. However, if the agrarian state does not have a deep hinterland to expand into, it may lose the scaling-up race to the nomadic polity, and is conquered by it. What is the balance of forces favoring cooperation of lower-level units and, therefore, their ability to combine into higher-level collectives? Here "units" and "collectives" are social groups at different levels of hierarchical complexity. For a society to grow in size, it has to make repeated transitions from the ith *to* $(i + 1)$th level. The success of each transition depends on the balance of forces favoring integration versus those favoring fission. Thus, evolution of traits promoting integration at the $i + 1$ level is favored by (1) increasing cultural variation among collectives and decreasing variation among lower-level units, and (2) increasing the effect of the trait on the fitness of collectives and reducing the effect at the lower level. Consequently, it is expected that large states should arise in regions where very different people are culturally in contact, and where interpolity competition (i.e., warfare) is particularly intense.

Instead of using computational theory to understand the evolution of complex political systems in history, Mezza-García et al. (2014) have refined computer theory in terms of what they known on hierarchical political systems. According to these authors, the similarity between a Turing machine and hierarchical political systems can be explained by how the transformation of 'inputs' into decisions in the latter is achieved, namely via sequential routes of rule-based activities that are assumed to take place in a closed manner amongst a selected group of individuals—the government. For those individuals who do not form part of the regime, and even for those who are members of a separate subsection of government, the computation of the decision takes place in a 'black box' until the moment of the 'halt' and the output of a political decision is made available. Decisions in such political systems are made with a type of information processing that works in a linear framework of reference, but which is limited when finding optimal solutions in spaces of high complexity. In the suggested model, heterarchical political organizations operate with decision-making dynamics whose computation is performed by an open system, i.e., that is in interaction with the world in various levels simultaneously in a distributed, parallel, diffuse, real time and decentralized manner. Inputs and conditions can be modified during the computation, and external agents can therefore also interact with this process. Ideally, 'outputs' or decisions are produced bottom-up from local interactions, rather than only implemented in a top-down manner at the expense of the complexity of human social systems and their environments.

As an example of computational models to understand the origins and formation of complex polities, Bogle and Cioffi-Revilla contribution to this volume (Chap. 13) implement a model about politogenesis in Sub-Saharan Africa. ZambeziLand demonstrates how a society of initially small and egalitarian groups could evolve into a complex society with a few large groups in response to changes in how individual members perceive their group and the state of extant leadership. The authors are interested in how ancient political centers originated and why they dissolved, analyzing sociopolitical phase transitions, whereby polities form and dissolve as people migrated to larger, more complex communities. The punctuated process of sociopolitical phase transitions, typical of polity cycling is explained by modeling the dynamic interplay among leaders and society members (individuals and groups) experiencing fluctuating conditions of leadership and loyalty during recurring times of stress affecting the local community. Larger and more complex polities were generated through a recursive, iterative process of collective action successes and failures by individuals and groups. The authors assume that the main structure of the fast process is universal and invariant, but the exact branching paths realized vary, depending on contingencies such as a situational change having endogenous or exogenous causes, a society perceiving or not the situational change, collective action occurring or not, success or failure in collective action being realized: hence, the term canonical. As situational changes recur in this particular society's model, a "fast process" punctuated by contingent events begins, including subsequent collective action choices made by society members (leaders and followers). Collective action may succeed or fail, depending on other contingent events. The outcome of each fast process results in the polity generating greater or lesser complexity when examined on a longer time scale or "slow process." Recursive fast processes occur relatively quickly as the society succeeds or fails in solving collective action problems that arise in the normal course of its history, with sociopolitical results and effects accumulating over time in the slow process. The most significant result of the Cioffi-Revilla and Bogle's model is the demonstration via computational simulation that an initially egalitarian, homogeneous society can quickly coalesce into a small number of much larger differentiated groups.

A similar approach applied to Inner Asia (Central Eurasia) in the past 5,000 years has been published by Cioffi-Revilla et al. (2007, 2013, 2015), Rogers (2013), Rogers et al. (2015). In all cases, the simulations are based on Cioffi-Revilla's computational theory for the emergence of social complexity accounts for the earliest formation of systems of government (pristine polities) in prehistory and early antiquity. The theory is based on a fast process of stressful crises and opportunistic decision-making through collective action. This core iterative process is canonical in the sense of undergoing variations on a main recurring theme of problem solving, adaptation and occasional failure. When a group is successful in managing or overcoming serious situational changes (endogenous or exogenous to the group, social or physical) a probabilistic phase transition may occur, under a well-specified set of conditions, yielding a long-term (slow) process of emergent political complexity and development. A reverse process may account for decay (Cioffi-Revilla 2005, 2009).

1.2.8 Simulating Social Life After Prehistory

As soon as we enter those historical periods in which written sources can be found, read and analyzed, the effort for a computational formalization of historical explanation is less evident in the current scientific literature. It seems as if the narrative basis of available data from the past constrains the causal explanation of this past imposing a similar narrative. As we have been suggesting all along this introduction, as in the rest of the book, the nature of available data from the past should not affect the logical form of the historical explanation in the present.

We can use agent-based models or any other algorithmic presentation of social mechanisms implied in the historical events whose causal relationships we intend to analyze. Obviously, the higher amount of data can force the researcher to change the scale of the analysis, moving for the quasi-abstract or theoretical social units considered in the case of hardly known prehistoric events, to more detailed social units, at better logical resolution, up to the level of the individual, if you have data about individual behaviors.

The exception to this apparent lack of interest in the computer simulation of ancient societies can be the study of the rise-and-demise of ancient empires, a historical subject that has been an important topic for computer simulation. Since the early days of authors like Hosler et al. (1977) and Dickson (1980), computer algorithms have been used to reproduce and to understand the collapse of ancient worlds (Lowe 1985; Renfrew 1987; Parisi 1998; Brunk 2002; Janssen and Scheffer 2004; Dalfes 1997; Hunt and Elliott 2005). Most of those methods used non-linear equations to model the way an economic system ceased to be efficient sometime in history. This is still an important area of research (Davidson 2010; Scarborough and Burnside 2010; Flores et al. 2011; Knappett et al. 2011; Reuveny 2012; Heckbert 2013; Heckbert et al. 2014; Faulseit 2015). Although of great interest, many of such studies seem to be too limited and are prone to be considered as overtly deterministic (Butzer and Endfield 2012). We need to go beyond the trivial relationship between ecology, natural resources and human society to really understand the highs and lows of historical trajectories.

There is a single contribution in this book related to the computer simulation non-prehistoric worlds for which we have appropriated written sources. Trescak et al. (Chap. 14) present a novel approach that can significantly decrease the cost and effort required for simulating everyday life of ancient inhabitants of virtual cities, while still capturing enough detail to be useful in historical simulations. The authors show how it is possible to design a small number of individual avatars and then automatically simulate a substantially large crowd of virtual agents, which will live their lives in the simulated city, perform choirs and rituals as well as other routine activities that are consistent with their social status. The key novelty of this approach that enables simulating such sophisticated crowds is the combination of physiological needs—for generating agent goals, emotions and personality—for choosing how to fulfil each goal and genetically informed propagation of appearance and personality traits—to propagate aspects of appearance and behavior from a small sample of manually designed individuals to large agent groups of a desired size. The usefulness of the approach is demonstrated by applying it to simulating everyday life in a reconstruction of the ancient city of Uruk, 3000 B.C. In the model, the authors have enriched computational agents with personalities and emotions, which affect their decisions when creating a plan for a current goal. This approach may even lead to emergent agent behavior that appears to be closer to human-like reasoning. As an example, the chapter details the case of a fisherman agent with no personality and emotions that catches fish when it's hungry. The agent will fish until it succeeds, or until it dies of hunger, unless the programmer manually specifies a possible change of plans when hunger level raises to a critical value. In contrast, the same can be computationally built by making the same fisherman having personality and emotions that may get frustrated when being hungry and unsuccessful. This agent may "decide" to stop fishing when frustration level overwhelms the rational decision for fishing and will search for alternatives to feed, such as begging or stealing food. The decision whether to beg or steal would depend on agent's personality.

In the previous example, fisherman represents a specific social group of the simulated population. Social groups combine certain classes of individuals that fulfill their goals in a similar way. Combining individuals into social groups allows the authors to define and program actions on a group level, rather than having to do this on individual level, reducing effort in defining crowd behavior. They consider again the case of an ancient Mesopotamian fisherman who has to trade fish with a spear maker in order to replace his broken fishing spear. The solution implies the explicitly formalization of social norms that, captures rules and protocols that drive agent interactions. As a result, agents can use these norms in reasoning to create plans for their current goal. This provides agents the ability to automatically perform their actions depending on their assigned social group. In order for agents to be able to select an action that is most relevant for their personality, such action has to be annotated by following personality facets: temptation, gregariousness, assertiveness, excitement, familiarity, straightforwardness, altruism, compliance, modesty and correctness. Using values of personality facets, the agent selects an action that provides the highest utility for its personality type. To define social groups, their actions and interactions, the authors specify virtual institutions that may have existed hypothetically in ancient Uruk in the form of an Organisation-Centred Multi-Agent System (OCMAS), establishing what agents are permitted and forbidden to do as well as the constraints and the consequences of their actions. In general, such virtual institution regulates multiple, distinct, concurrent, interrelated, dialogic activities, and each one involving different groups of agents playing different roles. In the presented case study, the authors defined all components of the Virtual Institution, with roles of fisherman, spear-maker, pot-maker, pries, king and wife.

Researchers at the University of Chicago and Argonne National Laboratory (Altaweel 2008; Altaweel et al. 2006; Altaweel and Christiansen 2004; Christiansen and Altaweel 2004, 2006; Wilkinson et al. 2007a, b, 2013) take a different approach for the historical understanding of ancient Mesopotamian societies. They have modeled the trajectories of development and demise of Bronze Age settlement systems for both the rain-fed and irrigated zones of Syria and Iraq. The reconstructed landscape near the ancient city of Assur is used as the example setting to test the effectiveness of simulated cultivation strategies. These methods include sole dependence on biennial fallow and rainfall, gravity flow irrigation, application of manure, and the integration of all these approaches. Results obtained within this computer model attempt to delineate agricultural constraints and potential benefits of the specific anthropogenic processes and strategies addressed. The investigation intends to prove that systems of ancient Near Eastern cities co-evolved in an intimate relationship with their environment, primarily by means of the aggregation through time of smaller fundamental units (e.g., households). The model allows for the scaling up of a settlement from a single household to a village, and ultimately to an urban center with its appropriate array of subsidiary and neighboring settlements. Agrarian production (specifically in light of environmental stresses) and social interaction is modeled at a mutually consistent, fairly detailed level that will support a realistic representation of feedback processes, nonlinear behavior mechanisms, and some degree of self-organization in Bronze Age settlement systems. Emphasis is on the development of the household model and its transformation into higher-order settlements. Everyday decisions in farming are also being incorporated into the model (e.g., when to plant, whether to fallow or crop annually, etc.), as well as social factors such as the pooling of resources. Moreover, the full model includes mechanisms that allow for the growth of social differentiation and that enable some households to grow and others to become subordinate.

The first empires in the Old World seem to be an ideal domain for computer simulation using historical information to calibrate the key model parameters. Palmissano and Altaweel (2015) have simulated explanatory models of settlement hierarchy in Central Anatolia during the Old Assyrian Colony period. Symons and Raine (2008) have investigated the spread of information and population aggregation in a somewhat ideal agrarian society based on an abstracted Egyptian landscape containing villages, flood plain, and river. The agents represent farming households which exchange information and migrate around the landscape motivated by the availability of surplus food (used as a proxy for quality of life). The model follows the aggregation of hamlets into larger villages that occurred during the pre-dynastic period. The results presented are intended to correspond to a one hundred to five hundred year time-span in the period roughly 3800–3300 BC. One of the drivers of Symons and Raine model is the variability of the Nile flood, since this determines the changing fertility of the land. The fertility is modelled as a function of perpendicular distance from the Nile. There are no records of land tenure in the pre-dynastic period. Therefore the authors have extrapolated back from later practice to implement a simplified form of land tenure. Thus, they have included in the model the ‘buying’ of fields whenever a village has more labor available than the fields it ‘owns’. Once bought these fields remain under the ownership of the village even if the population declines. For simplicity, ownership is assigned to a village as a whole, rather than to individual households. The algorithm to decide which fields to buy is based on three factors. The first is the fertility of the field. The second factor is the distance to the fields, which makes a field less attractive the further away it is from the village. The final factor is the undesirability of owning fields adjacent to those already owned, as an insurance policy against fluctuations in yield. A key feature of all of the simulated scenarios is the aggregation of population. The movement of the population towards the Nile and the abandonment of the more distant villages are to be expected on the grounds of the distribution of fertility. Each household simply tries to optimize their quality of life. As a result it turns out that they aggregate into larger villages. The outcome is not even the most desirable from the point of view of overall average quality of life for an individual household over time in any of the models. The movement of the population consumes resources and therefore reduces the overall quality of life, and the agglomeration into larger villages does not exploit the full potential fertility of the landscape. The driving force that produces larger village units is the unpredictable variability of the flood that provides relative safety in numbers.

The regions bordering the Aegean Sea were also witnesses of important historical events some 4000 years ago. Knappett et al. (2008) have created a spatial network model to understand the scale of cultural (and economic) interaction between the Cyclades, Crete, the Greek mainland, the Dodecanese and coastal Asia Minor during the later periods of the Middle Bronze Age (c. 2000–1600 BC). In this period, there appear to be substantial changes in transport technology between the Early Bronze Age and the later Middle Bronze Age, with the advent of the sail. The main hypothesis is that the centrality and size of the historic site of Knossos (Crete) and the growth of Minoanisation, may be related. The authors propose a mathematical model of 'imperfect optimisation' to describe such historical maritime networks, encoding, metaphorically, the notion of gravitational attraction between objects in space. The 'gravitation' in this case is a balance of social forces, expressed by networks with settlements of particular sizes and links of particular strengths. The model can be tweaked by giving different relative importance to the cultivation of local resources or to trade, and to show what happens when a member of the network suddenly disappears. The model incorporates some sense of function: regional interaction networks must accrue some benefit, balanced against their costs. Hence the model works on the assumption of some basic optimisation. Secondly, the model takes account of geographical distances while not being strictly determined by them. The model is neither fully bottom up like agent-based modelling, which tends to aggregate scales very coarsely, nor entirely top down; it is set up in such a way that the interactions between the level of the site and that of the network as a whole can be explored.

Investigating further in the same historical domain, Chliaoutakis and Chalkiadakis (2015, 2016) have developed a functional ABM system prototype for simulating an artificial ancient society of autonomous agents residing at the Malia area of the island of Crete during the Early Bronze Age. At its current implementation, the ABM allows exploring the sustainability of specific agricultural technologies in use at the time, so we can examine their impact on population size and dispersion; and it allows for the incorporation of any other technology that needs to be modeled. In addition, it allows us to assess the influence of different social organization paradigms on land use patterns and population growth. Importantly, the model incorporates the social paradigm of agents self-organizing into a "stratified" social structure, and continuously re-adapting the emergent structure, if required. The investigation is based on a self-organization algorithm incorporating a set of agent relations influencing the various social interactions, and a decentralized structural adaptation mechanism, suitable for open and dynamic organizations. Simulation results demonstrate that self-organizing agent populations are the most successful, growing larger than populations employing different social organization paradigms. Specifically, self-organization is compared to egalitarian-like and static hierarchical organization models. The success of this social organization paradigm that gives rise to "stratification" that is, non-egalitarian societies, and provides support for so-called "managerial" archaeological theories which assume the existence of different social strata in very early period; and consider this early stratification a pre-requisite for the emergence of the Minoan Palaces, and the hierarchical social structure evident in later periods.

Insights into historical region-wide political consolidation have been suggested by simulation results from an agent-based model based on historical data of human societies circa 2500 BC to AD 1000 in the Lake Titicaca basin of Peru and Bolivia (Griffin and Stanish 2007). The agents' behavior was modeled as micro-level condition-action rules based on the hypothesized causal factors of: agriculture, migration, competition, and trade. The approach to modeling political dynamics was inspired by Lars-Erik Cederman's agent-based Emergent Polarity model of early nation-state geopolitics (1997, 2002), which the authors adapted for pre-Inka historical scenario. This model simulated the consolidation of small polities into large ones which may then fission back into small independent entities and subsequently consolidate again, reminiscent of the recycling pattern observed in pre-state chiefdoms. The spatial end state of each simulation run has been classified as one of several alternative political configurations, based on the number of sovereign states remaining: unipolar, bipolar, multipolar, or nonpolar. In the same way, each simulation run of the current model was classified as one of seven alternative Titicaca political prehistories, one of which corresponded to what the record indicates to us actually happened. The authors have insisted in the temporal dimension to the classification scheme to distinguish not only the end state but the trajectory through time to reach that configuration.

Some models emphasize the key role of the interactions between households, institutions or spatial entities to generate a processual explanation of the emergence of a hierarchical urban system (Batty, 2001; Schmitt and Pumain 2013). In terms of transition, the model should simulate the transition from a loose position (random or uniform seeding of the entities) to the emergence of a spatial hierarchical and organized structurement without such an objective contained in the rules of model. Among the relevant models, we can mention the SIMPOP model, in which the settlement entities are the agents, the assumption being that there are interaction processes at the meso-geographic level that cause the trajectory of the settlement system in one direction rather than another. Starting from an initial situation in which we only count for agricultural villages poorly differentiated in function and size of cities emerging crescent acquire new functions and the possibility to exchange with broader geographic ranges. The growth or decline of a city will depend on the success of its trade with other villages and cities with which it interacts (Sanders et al. 1997; Pumain et al., 2009). The interference zones of influence of other cities creates a context of long distance competition in which the city must develop its position.

An interesting domain for applying these models to the historical formation of ancient cities is Greece. Rivers and Evans (2014) have re-examined the onset of centralisation in mainland Greek city states of the 9th and 8th centuries BCE. The aim is to model the onset of 'urbanisation', by which is meant the emergence of dominant settlements within community territories as a result of a transference of 'sovereignty' from villages to create larger associations centred upon these dominant settlements. The authors have compared two cost-benefit model in which the benefits arise from exchange between sites, assuming that larger sites getting most benefit from exchanging with larger sites. These non-linear benefits are offset against the cost of sustaining the network, assumed linear in the total network activity.

Around the 10th century BC, the rural villages in South Etruria (now Tuscany and Latium, Italy) began to disappear and a number of cities started to arise. The accepted grounds of these events deal with defense and safety reasons. Bianchi and Marcialis (2013) attribute the birth of the proto-cities to a sustainability crisis in the mining villages and asserts that mining technicians imposed such transition on farmers in order to carry out a sustainable reorganization of the whole system of settlements and, as a corollary, to strengthen their ruling role. The authors illustrate the proposed hypothesis by means of a simulation model roughly reproducing the described event. The model is based on the idea that the city birth can be interpreted as a discontinuity in the social system behavior. An unsustainable growth may have caused a crisis in the Etruscan village system. The formation of a new form of social aggregation, the city, would have achieved an organizational change and restored sustainability.

Ceconni et al. (2015), address the same historical case. In this simulation, the Etrurian territory is divided into a grid of square cells, with each cell characterized by three properties—(a) soil quality and presence of natural resources, (b) existence of water courses, (c) morphology of the ground from the point of view of defensibility—and the model assumes that each settlement decides what to do on the basis of these properties. The simulation reproduces the process that led to the appearance towards the end of the second millennium of a few large centers in well-defended sites and numerous small settlements. During each cycle of the simulation, each settlement (a) takes into consideration its *N* (number of inhabitants), (b) defines its zone of control with respect to the surrounding area, and (c) calculates how many resources are available for its inhabitants, resulting in the relative value of resources per capita. The simulation can develop according to two different types of dynamics; a positive and a negative dynamics. A positive dynamics means that the number of inhabitants of a settlement increases together with an increase in the size of its zone of control. Therefore, the available resources also increase and the value of the resources per capita remains high. The settlement is a prosperous one. On the contrary, a negative dynamics implies an increase in the number of inhabitants but not of the settlement's zone of control because of the presence of the zones of control of other settlements or because the zone of control is made of soil with low productivity. In this case, the resources per capita become insufficient, and the settlement is in trouble. When the resources do not meet the needs of a settlement's inhabitants, the number of inhabitant decreases and, if is reduced to zero, the settlement disappears. The virtual Ancient Southern Etruria appears to be divided into five main zones of control and four of these five zones of control correspond to the historical proto-urban centers of Orvieto-Volsinii, Tarquinia, Cerveteri and Veio. In the simulation, already during the virtual Early Bronze Age the system seems to undergo a collapse, going from 250 villages to about 60, while in the following centuries it remains roughly stable, with limited fluctuations. This diverges from what we know from the archaeological evidence which tells us that, after an increase between the beginning of the Early Bronze Age and Middle Bronze Age, the total number settlement remains pretty stable until, in the First Iron Age, the number of settlements is drastically reduced. This phenomenon is interpreted as due to a gradual but steady population growth but it is not captured by our simulation.

Crabtree (2016) has explored trade relationships between Etruscans and the native Gauls. She examines the first five centuries of wine consumption (from ~600 B.C. to ~100 B.C.), analyzing how preference of one type of luxury good over another created distinctive artifact patterns in the archaeological record. She has created a simple agent-based model to examine how the trade of comestibles for wine led to a growing economy and a distinctive patterning of artifacts in the archaeological record of southern France. This model helps shed light on the processes that led to centuries of peaceable relationships with colonial merchants, and interacts with scholarly debate on why Etruscan amphorae are replaced by Greek amphorae so swiftly and completely.

Heckbert (2013) has presented preliminary results from his MayaSim model, an integrated agent-based, cellular automata, and network model representing the ancient classical Maya social-ecological system (ca. 250–900 AD). The model represents the relationship between population growth, agricultural production, soil degradation, climate variability, primary productivity, hydrology, ecosystem services, forest succession, and the stability of trade networks. Agents representing settlements develop and expand within a spatial landscape that changes under climate variation and responds to anthropogenic impacts. The model is able to reproduce spatial patterns and timelines somewhat analogous to that of the ancient Maya. This investigation aims to identify candidate features of a resilient versus vulnerable social-ecological system, and employs computer simulation to explore this topic, using the ancient Maya as an example. Complex systems modelling identifies how interconnected variables behave, considering fast-moving variables such as land cover change and trade connections, meso-speed variables such as demographics and climate variability, as well as slow-moving variables such as soil degradation.

Watts (2013) has modeled some aspects of Hohokam economics. The Hohokam were an ancient Native American culture centered on the present-day US state of Arizona during the period AD 200–1450. The objective of this research has been to first identify a variety of economic models that may explain patterns of artifact distribution in the archaeological record. Those models were abstract representations of the real-world system reconstructed on the basis of microeconomic theory, and economic anthropology hypotheses. Those hypotheses have been implemented into an agent-based model, and run to assess whether any of the models were consistent with Hohokam ceramic datasets. The results su workshop procurement and shopkeeper merchandise, provided the means of distributing pottery from specialist producers to widely distributed consumers. Perhaps unsurprisingly, the results of this project are broadly consistent with earlier researchers' interpretations that the structure of the Hohokam economy evolved through time. Growing more complex throughout the Preclassic, and undergoing a major reorganization resulting in a less complicated system at the transition to the Classic Period.

Those investigations show the relevant paper of the advanced production economies in ancient times and how computer simulation allows reconstructing its functioning from incomplete and sometimes partial written sources from the past. Among the aspects we need to consider there is the practice of irrigation in ancient kingdoms to increase productivity. Irrigation systems, with their many entities, social and physical, their many interactions within a changing environment and emergent properties, are typical examples of systems for which agent-based modelling could yield fruitful analysis because of the highly detailed and complex relations between human actions and the social and material context. Ertsen (2011), Murphy (2012) and Altaweel (2013) show how interactions between humans, hydrology and hydraulics within irrigation systems have historically created patterns of water use. Both studies are based on a modelling-based approach generating flows in ancient irrigated environments, as it yields new insights in the way irrigation has succeeded in sustaining human civilization—or failed to do so, pointing out to the fact that we should not explain how irrigation-based societies collapse after centuries or even millennia, but why these societies did not collapse each and every day. It is the combination of modelling daily interactions by agents and water fluxes that will build better understanding of irrigation systems as anthropogenic landscapes resulting from activities of individuals, households, and groups, within hydraulic and hydrological boundaries setting the material context.

Kuznar and Sedlmeayer (2005) have developed a flexible agent-based computer simulation of pastoral nomad/sedentary peasant interaction that can be adapted to particular historical and social settings. The authors focus on how environmental and material factors may have conditioned individual agent response has allowed the modeling of how collective behaviors (mass raiding, genocide) can emerge from individual motives and needs. Many factors influence tribal conflict in the modern world (ethnicity, global politics). However, these simulations reinforce the analyses of some social scientists that argue such conflicts are the inevitable result of the breakdown of land use in the face of growing populations, marginal habitats, and an unprecedented ecological crisis. An alternative model has been offered by Cohen and Ackland (2012a b). Angourakis et al. (2014) have created an abstract agent-based model describing a mechanism of competition for land use between farming and herding addressed to understanding "oases" economic systems in historical central Asia. The aim is the exploration of how mobility, intensity, and interdependence of activities can influence land use pattern. After performing a set of experiments the authors compare the implications of each condition for the corroboration of specific land use patterns. In this way, the overall extension of farming in oases can be explained by the competition for land use between farming and herding, assuming that it develops with little or no interference of climatic, geographical, and historical contingencies.

A particular application of this way of studying the historical sources of inter-cultural conflict is Altaweel and Paulette (2013), who have investigated the long-term effects of economic interaction between nomadic and sedentary groups in the Bronze Age Near East. To keep things as simple as possible, they have modeled only a single, small sedentary community and a single nomadic group. The nomadic group visits the village for a portion of each year as a part of its annual migration pattern, and it is during these visits that economic exchanges take place. In a series of simulation runs, the authors varied the timing of the nomadic visit and the resources available to each group, and they tracked the impact of these changes on the economic life of the settlement and its inhabitants.

Cioffi-Revilla et al. (2007, 2010; see also Rogers 2013; Rogers et al. 2015) have simulated the rise and fall of polities in Inner Asia over a long time span, on the basis of nomadism effects on the economic, social and political structure. The time is defined as sufficiently long to include significant climate change. When climate changed, the biomass distribution on the landscape also changed, which in turn generated changes in the biological and social dynamics of animals and people, respectively. HouseholdsWorld is a spatial agent-based model of pastoral nomads living in a simple socio-natural system. The target system is a generic locality smaller than a region of Inner Asia shortly after ca. 500 BCE, the time period just prior to the rise of the Xiung-nu polity (ca. 200 BCE). The primary sources used for developing the HouseholdsWorld model were epigraphic, archaeological, ethnographic, and environmental, as detailed in the subsections below. Several of the patterns produced by simulation bear significant qualitative and quantitative resemblance to comparable patterns in the target system. For example, the distribution of wealth has the approximate form of a log-normal distribution, as a real-world distribution of household wealth usually should. Similarly, household movements show marked periodic fluctuations, as in the real world when nomads undergo seasonal travel following their herds. While the model does not attempt to produce a specific historical or empirically replicated replication, the overall qualitative and quantitative behavior of households, herds, and seasons are supported by known features of the target system.

Concerning the study of later periods in ancient times, there is a growing interest in modeling Roman economy in terms of micro-behaviors, feedback, and local interaction. Before anyone can ask questions about growth, or market integration, or the degree to which Rome was 'primitive' versus 'modern', some scholars are focusing on individual decision making and networks of individuals at all geographical scales and then using those networks as the substrate for computationally simulating individuals' economic activities (Brughmans 2012). The idea that network relationships (and the institutions that emerge to promote these) are the mechanism through which ancient economies deal with incomplete knowledge is a powerful one because we can find and outline the traces of these networks through archaeology. The simplest of these essays are those by Graham (2005, 2006) who has tried to understand the geography of the Empire from the point of view of a person traveling through ancient roads. The author takes the lists in the historical written Itineraries, and recast them as networks of interconnected cities. The purpose is to know whether there are any significant differences between provinces' connective network topography in terms of the transmission of information. One agent is given a piece of 'knowledge', which it may or may not share with those he encounters. The rate at which knowledge is transmitted therefore depends on the chance of transmission in any given encounter, and on the topology of the itinerary network. By controlling for the different variables, significant differences in how the different provinces' networks facilitate the transmission of information may be observed.

Graham and Weingart (2015) have developed an agent-based model of the Roman extractive economy which generates various kinds of networks under various assumptions about how that economy works. This simulation of an ancient economy is based on four key mechanisms: (a) the generation of small parcels of capital to combat risk; (b) little homogenization of products; (c) opportunism; and (d) social networks where there is high local clustering and a few long-distance links. These mechanisms correspond well with the archaeology of the Roman economy and the picture we know from legal and other historical textual sources. The authors have formalized in Netlogo code their ideas concerning how economic networks might be formed; they then sweep the parameter space, the entire landscape of possible outcomes; they compare that generated landscape of the model against known archaeological networks; and in the degree of conformity or disjuncture between the model and observed networks they reevaluate the stories that have been told about the past, creating new models in the process. They assume they will never be able to simulate perfectly the formation processes that give rise to a particular archaeological network. To do so would require making a map as large as the territory it is intended to describe. The computer translation of a hypothetical model of Roman economy, and the role of social networks within that model should be couched in all appropriate caveats and warnings. Networks can be discerned and drawn out from archaeology, prosopography, and historical sources. If we can align networks from the ancient evidence to those generated from the model's simulation of the ancient economy, we have a powerful tool for exploring antiquity, for playing with different ideas about how the ancient world worked.

Brughmans and Poblome (2016) take a very similar approach. They have presented an agent-based network model simulating the social networks which represent the flow of information and goods between roman traders. The concept of social networks is here used as an abstraction of the commercial opportunities of traders, acting as a medium for the flow of information and products. In the model 2000 traders are located at 100 sites and are connected in a social network. Four products are produced at four different 'production sites', and are subsequently distributed through commercial transactions between pairs of traders that are connected in the social network according to shortest-path-length links to reproduce the idea of "small world". Preliminary results suggest that the local-knowledge variable has a limited effect on the wideness of goods distribution, whilst the proportion of inter-site links variable has a strong effect. Limited commercial knowledge can still give rise to wide differences in distributions, but only in systems with highly integrated markets. This means that the local-knowledge variable is not instrumental in giving rise to the pattern of interest, whilst the proportion-inter-site-links variable is. Limited availability and high uncertainty of information, and a weak integration of different markets in an economy governed by supply and demand, is unlikely to give rise to large differences in the distribution patterns of commercial goods. Preliminary results of this model therefore reject the claim that limited market integration, availability and reliability of commercial information in ancient Rome gave rise to differences in the wideness of products' distributions.

It can be of interest to compare this new research on Roman economy with medieval and post-medieval economies. Ewer et al. (2001) have created a multiagent-based model to understand the role of deliberative Agents in Analyzing Crisis Management in Pre-modern Towns. The model distinguishes among merchants, craftsmen, laborers and local authorities. Agents interact as consumers and suppliers via several markets. Within the course of simulation local authorities are capable of intervening in market processes and implementing measures for crisis management. Hodgson and Knudsen (2008) have developed a behavioural explanation for the emergence of high levels of property rights enforcement in Europe in Medieval times (11th to 13th centuries). The merchant guilds have a central role in our explanation. The authors have developed an agent-based model that allows a number of important but previously unexplored issues to be considered (such as the joint importance of price variation, guild stability and the effect of uncoordinated embargo pressures among multiple guilds). The main result is that almost perfect levels of property rights enforcement can emerge solely as a result of multiple guilds' uncoordinated embargo pressures and medium to high levels of price variation. In fact, both conditions were fulfilled in the Middle Ages. In this model, no reputation mechanisms are required; our results solely depend on behavioural adjustment. High levels of property rights enforcement can emerge instead as a result of guilds' embargo.

Frantz et al. (2013, 2015) have studied the functioning of the Maghribi Traders Coalition—a historically significant trader collective that operated along the North African coast between the 10th and 13th centuries, which acted as a closed group whose interactions were governed by informal institutions. Bekar and Read have studied of eleventh and fourteenth centuries in England, when innovations in property rights over land induced peasants to respond by trading small parcels of land as part of their risk coping strategy (Bekar and Read 2009; see also Ewert and Sunder 2001 for a related experiment with trading networks in Medieval North Europe). Those times witnessed a dramatic increase in inequality in the distribution of peasant estimates of the quantitative impact of land trades (motivated by behavior toward risk) on the distribution of landholdings. The authors employ an agent based modeling strategy in which decisions regarding pooling, saving, labor supply, and land transactions are rule based. Agents are initially endowed with an exogenous landholding. Each period agent draws a harvest realization from a random normal distribution transformed by the requisite mean and variance. Harvests are independent across agents and through time. Agents pool and save out of current harvests. Smallholders work in the labor market; largeholders hire labor. Incomes are compared to a subsistence consumption bundle. An agent facing a subsistence crisis with a positive land position offers a parcel of land for sale. If, after depleting their land position, the agent is still below subsistence it experiences a subsistence crisis. An agent sufficiently above subsistence purchases parcels offered for sale. Agents sell land only when all other forms of insurance have been exhausted and they still face a serious subsistence crisis—treating land sales as an insurance mechanism of last resort. The authors test their explanation by simulating the dynamics of the land market, including differential reproductive success, partible inheritance, pooling and saving behavior, production parameters linking harvest realizations through time, crisis levels of income, wage rates, and land prices. Our simulations reveal that transactions in the land market coupled with population growth produce levels of inequality and skew consistent with those observed in the data. Population growth alone, coupled with partible inheritance, can only explain a small portion of the observed inequality.

Suárez and Sancho (2011) have investigated using computer simulations a theoretical model of cultural dynamics in which the individuals' behavior plays a strong role derives from the many cultural communities involved and the different scales used to study the spread of the baroque culture from Europe to America at the beginning of the Early Modern Period. The research explains the origins, evolution, transmission, and effectiveness of baroque artistic patterns, through the development of a model that rationalized the cultural and symbolic movements between Europe and Latin America, as well as the transformations and mutations that cultural objects undergo in their successive interactions with the variety of ecosystems and groups through which they pass on their journeys. The authors have created a Virtual Cultural Laboratory (VCL) using agent-based computational modeling that helps study how human culture has been historically transformed and transmitted through acts of learning, imitation, and the creation of cultural objects as they might be experienced by any human being from birth to death, independently of the specific community to which the cultural object or individual belongs. In general terms, the VCL addresses three different issues that are relevant for the historian and the cultural researcher. First, the VCL offers a platform to check on the effects of historical events and processes about which the researcher has comprehensive sets of data. Having the data lets the researcher to refine the model he is using to explain the given cultural and historic processes, as both data and model have to show a mutually coherent behavior. Second, when the researcher does not have good data about the phenomena he is studying, the VCL helps test the hypotheses and the assumptions used by the historian, and double-check the results of the simulation with the logic of those hypotheses. Third, the researcher can take advantage of the VCL by rehearsing different what-if scenarios that he knows did not happen, but whose results would be important to shed light into the context in which actual events took place.

But not only economic mechanisms should be taken into account for understanding social life in ancient times. The history of religion and the historical evolution of religiosity (Altran and Heinrich 2010; Whitehouse et al. 2012) can be an interesting domain for simulating historical non-economic dynamics. Czachesz (2007a, b) has advanced some algorithmic models of social behavior for understanding religiosity and look for ways of applying such models to the emergence of early Christian religion. The author puts forward the hypothesis that religious ideas emerge as a necessary consequence of the sophisticated "flocking" rules of human societies. Religion emerges from the interaction of a great number of participants with each other and their environment. Rituals are repetitive actions that emerge from these interactions. Texts (public representations) are environmental components that have been formed by the agents. Beliefs and experiences are generated by texts and rituals and describe the internal states of the agents. On a different level, however, also beliefs and experiences can be studied as distributed phenomena, inasmuch as they are emerging from the interaction of different parts within the human mind. His suggestion is that religious ideas emerge as a necessary side-effect of the sophisticated "flocking rules" of human societies. The large-scale dynamics of human societies emerge as agents make decisions based on interactions with our neighbors as well as on simulations of unknown, distant, and foreign human individuals. Some of the latter simulations are maintained in stabilized, stereotyped, and socially transmitted forms, such as national stereotypes. Ideas of religious agents are long-standing, stabilized, stereotyped, and socially transmitted simulations of distant or abstract persons. Religious agents, in fact, are often important family members, rulers, or distant, exotic people.

On a similar subject, Turchin (2003) has explored three alternative mechanisms of religious conversion and ethnic assimilation through history: the noninteractive, the autocatalytic, and the threshold models. Each model predicts a qualitatively different trajectory (the proportion converted/assimilated as a function of time). This means that using a model the historian can determine which theory better reflects the reality if he/she can find data on the temporal course of conversion. When fitting the model with historical data on conversion to Islam in Iran and Spain, results strongly supported the autocatalytic model and were nothing like trajectories predicted by the two alternatives. Turchin concludes from this result that all models are by definition wrong, because they oversimplify the complex reality, but the autocatalytic model is less wrong than the alternatives. It appears that the assumptions of the conversion process built into the autocatalytic model capture some important aspect of the historical reality of those territories at that time: once world religions got going, they generated a kind of momentum that allowed them to expand at approximately constant (per capita) rate. Dramatic events—world wars, imperial collapses, and nomadic invasions—did not derail these massive macrohistorical processes, at least in these particular cases (of course, certain kinds of events, such as the Christian Reconquista in Spain, are capable of reversing the tide of religious conversion).

Tomlinson (2009) has studied how ancestor veneration and other forms of commemoration may help to reduce social distance within groups, thereby encouraging reciprocity and providing a significant survival advantage. In his simulation, a prototypical form of ancestor commemoration arises spontaneously among computational agents programmed to have a small number of established human capabilities. Specifically, ancestor commemoration arises among agents that: (a) form relationships with each other, (b) communicate those relationships to each other, and (c) undergo cycles of life and death. By demonstrating that ancestor commemoration could have arisen from the interactions of a small number of simpler behavioural patterns, this simulation may provide insight into the workings of human cultural systems, and ideas about how to study ancestor commemoration among humans.

As examples of other non-economic models for understanding ancient worlds, we can mention a simulated Polynesian society that has been used to explain why, in Polynesia, growing stratification did not result in a devaluation of women's status, as most theorists had suggested (Small 1999). The computer model used to explore this problem—called TongaSim—attempts to emulate the basic social dynamics of Tonga, a Western Polynesian society. The program is capable of simulating the operation of a chiefdom with up to 100+ chiefly lines whose descendants marry and have children, create and maintain kinship relationships, exact and pay tribute, produce and redistribute agricultural wealth, expand in territory and go to war, and attempt to gain personal and group status. TongaSim was used to simulate the effect of warfare (a prime mover of stratification) on women's status, specifically the custom of "fahu" that asserts the spiritual superiority of sisters and sister's lines over brothers and their lines. Because of intermarriage patterns, this custom also serves to make higher status chiefly lines superior in kinship to lower status chiefly lines and, thus, supports traditional political power. The simulation showed that, despite the initial conflict between the interests of rising military chiefs and the fahu custom, the custom was appropriated by these rising chiefs, turning fahu's political effects "on its head." Ultimately in the simulation, the fahu custom provided a vehicle for military chiefs to gain status and power. This, it is argued, is consistent with the lack of any historical evidence that the fahu was challenged and toppled during periods of growing warfare and stratification.

In a related way, Froese et al. (2014) have simulated the political life in ancient Teotihuacan, México, from 100 AD to 500 AD. The authors have devised a mathematical model of the city's hypothetical network of representatives as a formal proof of concept that widespread cooperation was realizable in a fully distributed manner. In the model, decisions become self-organized into globally optimal configurations even though local representatives behave and modify their relations in a rational and selfish manner. This self-optimization crucially depends on occasional communal interruptions of normal activity, and it is impeded when sections of the network are too independent. The authors relate these insights to theories about community-wide rituals at Teotihuacan and the city's eventual disintegration.

Livni and Stone (2015) have simulated some aspects of pre-monarchic life in iron Age Israel, taking into account the potential cultural, civic, and social role of religious rituals and beliefs (i.e., the weekly Sabbath), in controlling deviation from social norms. The model begins with an analogy between spread of transgression (defined as lack of conformity with social norms) and of biological infection. Borrowing well-known mathematical methods, the authors have derived solution sets of social equilibrium and study their social stability. The work shows how a particular ritual in a complex polity could in theory enhance social resilience. The examination reveals that an institutionalized ritual had the potential to ensure a stable organization and suppress occasional appearances of transgression from cultural norms and boundaries. Subsequently, the model is used to explore an interesting question: how old is the Sabbath? The work is interdisciplinary, combining anthropological concepts with mathematical analysis and with archaeological parallels in regards to the findings.

War and violence have been regarded as relevant aspects for understanding historical evolution and social change (Younger 2012; Turchin et al. 2013). As a result of this interest in the formal study of conflict in ancient times, the computer replica of ancient battles has been one of the recurrent subjects of computer simulation (Cederman 2003; Stover 2007; Graham 2009; Findley 2008; Findley et al. 2010; Stilman et al. 2011; Craenen et al. 2012; Loper and Turnitsa 2012; Wittek and Rubio-Campillo 2012; Sabin 2012). War in the origins of humanity (Philips et al. 2014), during the Neolithic (Duering and Wahl 2014), the Trojan War (Flores and Bologna 2013), in roman times (Rubio-Campillo et al. 2015), in the medieval period (Murgatroyd et al. 2012) or later (Girardin and Cederman 2007; Rubio-Campillo et al. 2013) has been simulated. Models of ancient and modern armies can be then used as a virtual laboratory, where different hypotheses are tested under varying scenarios what allows the study behavioral action at any scale, involving tens of thousands of agents within the context of modelling logistical arrangements relating to the battle, or taking into account how the resilience of formations to combat stress may increase exponentially when they contain just a small percentage of homogeneously distributed individual agents (warriors) with higher psychological resistance. In this way, the computer model of a battle can show different possible courses of action, the influence of random movements, the influence of landscape, the consequences of the differences in weaponry or soldiers training, logistics and the “geniality” of generals and commanders. Distributed simulation is the only viable approach to deal with a problem of such scale and complexity.

The other side of violence is mortality. Computational simulation can be the most obvious way to explore the consequences of famines in historical perspective, be there the result of violence, structural problems of the economic mechanisms or climatic transformations (Watkins and Menken 1985; Wassermann 2007; Curran et al. 2015). Ewert et al. (2003, 2007) have explored using agent-based technology the relationship between hunger and early market dynamics in order to understand the consequences of mortality crises in Pre-Modern European towns explains how to implement a model in which historical famines may be simulated. Zhang et al. (2011) considers the role of climate-change.

Mortality can also be the result of epidemics. Black Death in the middle ages is one of the best known historical examples (Bossack and Welford 2015). Voigtländer and Voth (2013) have simulated how a major shock to population can trigger a transition to a new steady state with higher per-capita income. The Black Death was such a shock, raising wages substantially. The model shows that demand for urban products increased and urban centers grew in size. European cities were unhealthy, and rising urbanization pushed up aggregate death rates. This effect was reinforced by diseases spread through war, financed by higher tax revenues. In addition, rising trade also spread diseases. In this way higher wages reduced population pressure. The authors suggest in a calibration exercise that our model can account for the sustained rise in European urbanization as well as permanently higher per capita incomes in 1700, without technological change. Europe's precocious rise to economic riches can be explained as the result of complex interactions of the plague shock with the belligerent political environment and the nature of post-medieval cities. Other related approaches to the computational investigation of the social, political and economic effects of historical epidemics are Duncan et al. 1993; Lagerlöf 2003; Monecke et al. 2009; Gaudart et al. 2010; Kausrud et al. 2010.

1.2.9 Simulating the Recent Past

There are two key factors that can be used to fix the begining of "modernity": industrial revolution at the end of 18th century and the French revolution and the posterior historical trend towards parliamentary political regimes. The Industrial Revolution was the transition to new manufacturing processes in the period from about 1760 to sometime between 1820 and 1840. This transition included going from hand production methods to machines, new chemical manufacturing and iron production processes, improved efficiency of water power, the increasing use of steam power, and the development of machine tools. It marks a major turning point in history; almost every aspect of daily life was influenced in some way. In particular, average income and population began to exhibit unprecedented sustained growth, but also new forms of inequality emerged. Only some aspects of this series of historical events have been explored using computational methods (but see Atack 1979; Komlos 1989; Komlos and Artzrouni 1994; Foley 1998; Malerba et al. 1999 and Garavaglia 2010; Spaiser and Sumpter 2016). Harley and Crafts (2000) used a classical computational general equilibrium (CGE) trade model with diminishing returns in agriculture and realistic assumptions about consumer demand. Their results show that while technical change in cottons and iron were major spurs to exportation of those specific goods, the need for food imports also stimulated exports generally. In any case, why did England industrialize first? And why was Europe ahead of the rest of the world? To answer these questions, Voigtländer and Voth (2006) built a probabilistic two-sector model where the initial escape from Malthusian constraints depends on the demographic regime, capital deepening and the use of more differentiated capital equipment. Weather-induced shocks to agricultural productivity cause changes in prices and quantities, and affect wages. In a standard model with capital externalities, these fluctuations interact with the demographic regime and affect the speed of growth. Voigtländer and Voth model has been calibrated to match the main characteristics of the English economy in 1700 and the observed transition until 1850. The authors capture one of the key features of the British Industrial Revolution emphasized by economic historians—slow growth of output and productivity. Fertility limitation is responsible for higher per capita incomes, and these in turn increase industrialization probabilities. Simulations using parameter values for other countries show that Britain's early escape was only partly due to chance. France could have moved out of agriculture and into manufacturing faster than Britain, but the probability was less than 25 %. Contrary to recent claims in the literature, 18th century China had only a minimal chance to escape from Malthusian constraints (Zhou 2008). This line of enquire has also been further explored by Galor et al. (2009), Desmet and Parente (2012), Mejía Cubillos (2015). Social aspects of emerging inequality as a consequence of industrialization have been explored by Crayen and Baten (2010). The third industrial revolution that is the transition to the Information Age has been computationally explored by Veneris (1990).

The French Revolution of 1789 was much more than a mere uprising of the "people" against the State. Its historical relevance comes from the fact that the main guidelines for the future parliamentary forms of government were defined then (Sharp and Weisdorf 2012). Why some street fighting in Paris at that time could have had so enduring consequences? Although there is not any specific computer simulation of what happened in France at the end of eighteenth century, we may suggest a general model of a social revolution based on a conjunction of events that were, themselves, and each independently caused (Grossman 1991). These events would include state crises, popular uprisings and elite actions. As they unfolded, these events may have been shaped by international forces that would have impinged on the states in question. In response to these events, the state and other elite actors may have found themselves constrained by some crisis (typically financial, often deepened by the exigencies of war) and therefore increasingly susceptible to the revolutionary challenges. The role for quasi-independent social actors, and the historically unique forms and sequencing of events can make the model suppler, and better able to represent diverse scenarios than prior theories. As an example, we can consider the MASON RebeLand model (Cioffi-Revilla and Rouleau (2010), based on: (i) an explicit polity model with politically complete structure and processes; (ii) social and natural model components within integrated socio-natural systems; and (iii) generative dynamics where insurgency and the state of the polity (stable, unstable, failing, failed, and recovering) occur as emergent phenomena under a range of social and environmental conditions.

In other words, instead of "reproducing" the "storming of the Bastille" or the activities of Robespierre and his committee of Public Safety we can "calibrate" an abstract model of the causal factors of insurrection, civil conflict and political transformation with empirical data from historical sources. This approach was suggested by Sewell (1985), Skocpol (1985), Goldstone (1991), and computationally enriched by Squazzoni (2008a, b), Cederman et al. (2010), Sallach (2010), and Altaweel et al. (2012). In this way, we can investigate the outbreak of different historical situations (Hermann and Hermann 1967; Bremer 1977; Mintz 1981; Hanneman 1988; Schrodt 1988; Chadwick 2000; Fogu 2009). Beyond the emergence of social conflict, revolutions and uprisings, the historical process towards parliamentary political regimes can be formally explored using computational tools (Cederman 2001, 2005; Ulfelder and Lustik 2007). The historical origins and emergence of political democracy should be studied as a macro-historical process that expanded from a small number of democracies to about 50 % of all states. In order to account for this development, Cederman and Gleditsch (2004) introduced an agent-based model combining natural-selection logic with adaptive mechanisms of regime change. The latter is implemented as an empirically calibrated, contextual rule that prompts democratization as an *S*-shaped function of the democratic share of a state's immediate neighborhood. A similar transition rule governs regime change in the opposite direction. The computational results show that regime change and collective security are necessary to produce realistic trajectories of democratization at the systemic level.

Kroneberg and Wimmer (2012) have explored some historical aspects of France socio-political evolution from 1500 to 1900. They have analyzed in formal and computational terms the conditions under which political modernization lead to nation building, to the politicization of ethnic cleavages, or to populism by modeling these three outcomes as more or less encompassing exchange relationships between state elites, counterelites, and the population. The authors show how social actors seek coalitions that grant them the most advantageous exchange of taxation against public goods and of military support against political participation (see also Wimmer 2014).

Sandberg (2011) and Jansson et al. (2013) have experimented system dynamics for studies of the global diffusion of democracy from 1800 to 2000. The dynamic explanation proposed focuses on transitions to democracy, soft power, and communication rates on a global level. The analysis suggests that the transition from democratic experiences ('the soft power of democracy') can be estimated from the systems dynamics simulation of an extended adoption-of-innovations model. Soft power, fueled by the growth in communications worldwide, is today the major force behind the diffusion of democracy. The findings indicate the applicability of system dynamics simulation tools for the analysis of political change over time in the world system of polities.

These are not the only historical subjects that can be explored using computational simulation tools and techniques. The amount of information coming from sources as historical census has allowed an interest for simulating demographic trends from the recent past (Silverman et al. 2011, 2014). An early example of this trend is Whitmore's work on simulating Amerindian depopulation in colonial Mexico (Zubrow 1990; Whitmore 1992). Gonzalez-Bailón and Murphy (2013) have built an agent-based simulation, incorporating geographic and demographic data from nineteenth-century France, to study the role of social interactions in fertility decisions. The simulation made experimentation possible in a context where other empirical strategies were precluded by a lack of data. The authors evaluated how different decision rules, with and without interdependent decision-making, caused variations in population growth and fertility levels. The analyses show that incorporating social influence into the model allows empirically observed behavior to be mimicked, especially at a national level. These findings shed light on individual-level mechanisms through which the French demographic transition may have developed. Bar and Leukhina (2010) have worked on the demographic transition related with the industrial revolution (see also Skirbekk et al. 2015). Going beyond pure demographic models, Wu et al. (2011) have created an agent-based simulation of the spatial evolution of the historical population in China. (See also Zhao 2000).

Also related with the modeling of population trends in the recent past, there is an increasing interest in historical changes in land use as a subject of computer simulations to understand the evolution of modern cities and urbanization processes (Ruggles 1993; Zhao 1994; Parker et al. 2003; Manson 2005; Matthews et al. 2007; Entwisle et al. 2008; Rindfuss et al. 2008; Arce-Nazario 2007; Bretagnolle and Pumain 2010; Komlos and Kim 1990; Le et al. 2010; Fu et al. 2010; Long et al. 2014; Magliocca et al. 2015; Chang-Martínez et al. 2015; Heppenstall et al. 2016). In many cases, cellular automata and agent integrated models are developed based on the prior research of to simulate land use and cover change. In such integrated cases, every cell is used to store the land use change related information of the location where the cell posits, and sense the land use change information of the cells in the neighborhood. Agents, with different roles, calculate the information stored in the cells and do the logistic decision of whether the cells change their states. Therefore, the model has capability of complex computation and a global dynamics.

Gasmi et al. (2015) propose a methodology to build agent-based models of the management of floods in Hà Nội (Việt Nam) in 1926. The authors have collected, digitized and indexed numerous historical documents from various sources, built a historical geographic information system to represent the environment and flooding events and finally designed an agent-based model of human activities in this reconstructed environment. They then show how this model can be useful to understand the decisions made by the different actors during this event, testing multiple scenarios and answering several questions concerning the management of the flooding events.

A possible criticism about the idea of simulating the past and the analytical explanation of social dynamics that generated our social, economic, political and cultural present would be the impossibility of simulating the historical evolution of complex polities in modern times for reasons of scale: to be fully capable of understanding historical dynamics of ancient empires and modern nations we would need to create artificial societies of such complexity that any computer could run the simulation. Nevertheless, the current use of agent-base modeling and related techniques to understand modern economics and modern social and political organization clearly indicates the opposite. If we consider the number of actual publications, it would seem that simulating the present is easier than simulating the past, and that simulating the recent past should be easier than simulate the most ancient human societies (Tesfatsion 2002; Batty 2007; Squazzoni 2012; Cioffi-Revilla 2014).

The amount of qualitative and quantitative historical data about the recent present may allow the historian-computationalist to go beyond the generic and abstract scales we have detailed up to now (households, families, communities, institutions, etc.) and introduce the replica of real people that once existed and we know for certain what they really did. Saqalli and Baum (Chap. 8) suggest the idoneity of two general scales for the computer simulation of social dynamics:

- The level of the village/hamlet (defined here along the more adequate word "terroir") unit is often used because it is the functional unit of management of a landscape, the geographic expression of a combination of rationalities that have to interact altogether. Building a model of one simulated entity below this level is impossible regarding the importance of such interactions, both direct (marriages and other social interactions but also mutual manpower support for instance). Roughly, it is the level in which micro-economic rationality can be considered in order to analyze and explain differences in the use of natural resources;
- The level of the territory that corresponds to a culture or a group of cultures. Roughly, it is the level in which macro-economic rationality can be assessed, assuming a certain homogeneity regarding the use of natural resources within this culture comparing to others. A main aspect here is to analyze the impacts of a homogenous use of these resources;

Would it be possible going beyond those general scales? Some experiments have been published to consider the historical simulation at the level of the individual. Yang et al. (2010) propose the use of a pattern oriented inverse simulation (PIS) to analyze a particular family line with more successful candidates in the civil service examination in imperial China. Two relevant patterns observed in the real family system are employed to decode family strategies along such an elite family line. The authors implemented PIS through inverse simulation techniques, by fitting the simulated results to the real genealogical data arranged in time-series as patterns. In case all those techniques allow us to use the individual as a real unit of analysis in a history study, then can we simulate the past at the level of what historic people really did? For instance, can we create a model for European artistic development in the last centuries with virtual simulations of known artists and musicians? We have detailed life stories of those individuals and given the current technology of agent based systems, there is no doubt that we can recreate the world, understanding individual behavior (Düring et al. 2011; Novak et al. 2014). Some pioneering work on this line has been initiated by Schich et al. (2014), Medina (2014), Park et al. (2015). The same could be made for other historical events, like World War II, from the point of view of Churchill, Himmler, Guderian, Montgomery, Eisenhower or any private that we know fought on that war and whose actions affected other people (see Alexander and Danowski 1990; Wetherell 1998; Gould 2003; Lemercier 2005, 2012; Boyer 2008; Hamill and Gilbert 2009).

Simulating historical events in full detail can be enormously costly, however. Therefore most computer simulations today vary the detail at which they simulate various events. In general, the level of detail appropriate for any one place depends on how much more expensive it is to produce such detail, and on how influential larger errors are in producing errors in the final results of interest. Since it is harder to vary the simulation detail in role-playing simulations containing real people, these simulations tend to have some boundaries in space and time at which the simulation ends (Hanson 2001).

1.3 Predicting the Future

As it has been shown all along this introductory chapter, the use of simulations that integrate disparate quantitative time series data and other time-oriented information into a unified formal presentation can reveal patterns, causes, probabilities, and possibilities across complex social, technological, economic, and political systems. Cycles, waves, logistics curves, and other archetypal patterns, when laid over historical data, can provide a deeper understanding of the dynamics of change. Timelines and these archetypal change patterns can also be used in the study of human change in the long run. In fact, a big number of publications are addressed precisely to this goal (Korotayev 2005, 2006; Korotayev et al. 2014; Grinin 2012; Grinin and Korotayev 2009; Sulakshin 2010; Hazy and Ashley 2011; Broadberry 2012; Foreman-Peck 2014; el-Muwaqqar 2014). Beyond the obvious interest of this endeavor for understanding the logic of the present in which we live in terms of the dynamics on very long periods of time, we need to ask whether we can go beyond and make the biggest question: would it be possible to predict the future given that we have already simulated the historical period that brought us until the present? In the last few decades, the reality of global changes has led many areas of science to explore possible futures. Public awareness and demand are indeed now pressing for clear results and tools to facilitate decision making.

One of the most influential arguments against scientific history was formulated by the philosopher Karl Popper (1957). Popper's main point was that because the future course of human history is critically affected by the development of knowledge, and because future scientific and technological discoveries cannot be predicted, a predictive science of human history is in principle impossible. However, the notion of *prediction* in science is not limited to forecasting the future. The paradigmatic example is the weather, which cannot be forecast more than 7–10 days in the future, even though we perfectly well understand the laws of hydrodynamics underlying weather fluctuations. However, because the dynamical system governing weather is in a chaotic regime and our measurements of initial conditions are not infinitely accurate, long-term prediction of weather is impossible.

In fact, the future is in principle unpredictable. In social life rare events with huge consequences, occur with greater frequency than in purely physical applications (Taleb 2010). The difference, however, is quantitative, not qualitative. Bridges collapse, space shuttles explode, and hurricanes strike from seemingly blue skies. However, we do not decide, on the basis of such prediction failures, that there are no laws of physics. Prediction is an inherent part of science, but not in the narrow sense of forecasting the future. *Scientific prediction* (to distinguish it from the common usage, which is closer in meaning to "prophecy") is used in empirical tests of scientific theories. Scientific prediction inverses the logic of forecasting: whereas in making forecasts we assume the validity of the underlying theory and want to know what will happen to observables, in a scientific prediction exercise we want to use the degree of match between observables and predictions to infer the validity of the theory (Turchin 2008, 2011).

Thinking about the future can take numerous forms, varying from planning actions to foreseeing possible scenarios by means of knowledge and informed guesses, or speculations and intuitions, or imagination and creativity (Von Stackelberg 2009; de Vito and Della Sala 2011). We are limiting the possibilities here to what can be formally extrapolated from the knowledge of the past. If there some kind of linearity in the dependence relationships empirically determined between temporally ordered events, we can extrapolate new events using linear and non-linear multiple regression statistical methods (Kantz and Schreiber 2004). Obviously, nothing in historical dynamics is so easy, and here unpredictability seems to reign. According to Hunemann (2012), the idea of future predictability intuitively means that when the initial state of a system is changed, there is some polynomial function of the predicted result that would yield the correct prediction for the subsequent new final state. Imagine a system with a given initial state (i), i.e., an initial value of the descriptive state variables or initial position in the state space, and a small range (d) of values around those initial values. This system allows predictions if the final values it reaches, starting from all different initial values in $[i - d; i + d]$, are in a range $f(d)$ which is not too much larger than the range (d) of initial values. If not, it means that the margin of error (represented here by d) of measurements of those initial values will not ensure that the final result yielded by calculating the final state is in a same or analogous margin of error, so there will be no possible prediction. If the future is unpredictable, then tracking down the causal trajectory of one event in the present will quickly become computationally intractable and thus impossible.

To our surprise, many aspects of human life can be extrapolated to some comparatively near future using relatively simple statistical models. This approach has had certain success in economy, as a side effect of path analysis studies (Nelson and Winter 1982; David 2001; Garrouste and Ioannides 2001; Höjer and Mattsson 2000; Martin and Sunley 2006; Vergne and Durand 2010). Chen et al. 2003 have presented a novel methodology for predicting future outcomes that uses small numbers of individuals participating in an imperfect information market. By determining their risk attitudes and performing a nonlinear aggregation of their predictions, we are able to assess the probability of the future outcome of an uncertain event and compare it to both the objective probability of its occurrence and the performance of the market as a whole.

In the same way, the future of political issues can also be examined from the point of view of the directed temporal dependencies among a set of social or cultural events. Relevant here is the pioneering work by Douglass North (1994), who generalized path dependence analysis making it the basis of a theory of institutional change. North's translation of the path dependence thesis to institutional change associates historical continuity of all kinds with the path dependence conception. The path dependence thesis serves as an explanation for long-term stability of institutions with different degrees of success and for the predominance of technologies and products, the optimality of which is called into question. The arguments primarily turn against economic equilibrium models in which efficiency is achieved in a state of equilibrium. They are also directed against the notion that "perfect" markets ensure efficient institutions ("invisible hand"). The currently very intense discussion of the path dependence concept in the social sciences is particularly influenced by the work of political scientist Paul Pierson (Pierson 2000; Kay 2005; Howlett and Rayner 2006; Schrodt 2006; Attinà 2007; Brandt et al. 2011; Schreyögg et al. 2011). As an example, we can quote the research work by Bechtel and Leuffen (2010) forecasting European Union politics using time series analysis. Authors like Bennet (2008), Bhavnani et al. (2008), Rost et al. (2009), Ward et al. (2010), Braha (2012), Schrodt et al., (2013) have used agent-based computational framework for predicting the onset and duration of civil wars as a consequence of the particular dependence between natural resources, ethnicity and politics. These investigations attempt to provide the policy making community with systematic ex ante forecasts of political events and trends (Agami et al., 2008; Schneider et al. 2010).

Visualizing possible futures of humanity is no more a science fiction dream (Kelly and Kelly 2002; Bishop et al. 2007; Duinker and Greig 2007; Schubert 2015; Zackery et al. 2015). The Integrated History and future of People of Earth (IHOPE) initiative is a global network of researchers and research projects with the goal of projecting, with more confidence and skill, options for the future of humanity and Earth systems. These projections will be based on models that have been tested against the integrated history and with contributions from knowledge of the Earth's integrated record of biophysical and human system changes over past millennia and tested human-environment system models against the integrated history to better understand the socio-ecological dynamics of human history (Costanza et al. 2012; Braje 2015). And this is not the only project for developing possible future scenarios that can be considered the consequences of what we are doing now, and what our ancestors did before us (Hajkovitz et al. 2012).

Anticipating the future is both a social obligation and intellectual challenge that no scientific discipline can escape. In any case, we should ask whether the future of human events will resemble what we know about the past. The use of formal computational and mathematical approaches does not impose such conclusion, because the same causal mechanism can produce different consequences according to the local circumstances. After all, the extrapolated future is just a probabilistic prediction and not a real fact (Tetlock 1999): once a relevant path has been defined between successive events, when looking into the future, the degree of predictability gradually goes down the further we look and uncertainty goes up. In the very short-term, predictability may be high and forecasting is the working planning mode of choice. In the very long term, everything is uncertain and attempts to planning demonstrate diminishing returns. In the middle zone, there is a level of predictability nut, considerable uncertainty scenarios (Kaivo-oja et al. 2004). Whatever the specific definition, the common denominator of any kind of prediction is a reference to the future. This implies that all sources of uncertainty associated with describing present and past must also be associated with forecasting —and one more: the specification error inherent in the future dimension. In particular, this error should be associated with the distinction between causality and correlation, i.e., the understanding of behavior, the necessary prerequisite for prediction. Thus, the key representational problem, the gap between model and reality, and the conditions for controlling that gap, becomes particularly evident in forecasting (Strand 1999).

1.4 Conclusions. Rethinking the Way the Past Can Be Made Understandable

As suggested by Saqalli and Baum in their contribution to this volume (Chap. 8), three goals may be assigned to modelling past social dynamics: describing, understanding and predicting. As it is the fate of history and archaeology to draw conclusions on a sometimes very narrow database, because we hardly know everything having happened years, centuries or millennia ago, it is necessary to continuously develop and adapt hypotheses to conceptualize the most probable historical scenario proposals and to eliminate the less plausible ones, the overly too simplistic, such as the one “single cause” cliché (climate, volcano, flood). This is possible, because a wide range of historical scenarios may be reconstructed by varying certain input parameters. In the computer, we would explore (by altering the variables) the entire possible range of outcomes for different past behaviors. The idea is then simulating inside a computer what we know about actions having been performed in the past and experimenting with the effects they may produce in such a virtual world. History runs only once. However, in the computer, it can run over and over again.

By conceptualizing a dynamical and extensible simulation platform, researchers and domain experts are provided with a tool for specifying and formulating own hypotheses, assumptions and discoveries (Timm et al., Chap. 2). Crucially, the simulation itself is claimed to carry the central explanatory role: it is the fit of the generated data, or the identification of generating agents and their rules of behavior, that purportedly does the explaining. The simulation either may provide a test of the models and its underlying theory, if any, or may simply allow the experimenter to observe and record the behavior of the target system. As the emphasis shifts from describing the behavior of a target system to the proper understanding of social systems through time, so the objective of historical research changes to the experimental manipulation of a possible scenario. With the possibility of constructing artificial systems reproducing in silico what the scientist believes people did in the past, a new methodology of scientific inquiry becomes possible. In this model of research, the target is no more a natural society but an artificial one, existing only as lines of computer code, and giving the idea of social activity. The value of creating artificial societies is not to create new entities for their own sake, but observing theoretical models performing on a testbed.

A common place of development of the historical simulations should be this focus on the understanding of the processes underlying social change, the evolution of the simulation with the representation of stability and change of social simulated process. May be this is what really matters to us, understanding the process and not only making emphasis on the results and the possible predictions of the models. The way an economist or a sociologist mainly seek to understand analytical results to understand the models is a clear example. To simulate is to understand how a model behaves, a social historical model is a formalization of an historical explanation and it is also the explicitation of all the assumptions implicit in the proposed model. The main value of creating artificial societies is not to create new entities for their own sake, but observing theoretical models performing on a testbed.

Computer simulation imitates the past through a computer reproduction of individual actions of agents, in response to a historically justified calibration of the virtual world in which they moved (Caughey 1972). Thus computed results are obtained as the effects of individual actions in a virtual environment and the impact that these environment has over the agents. The fact that the results "fit" with the empirical description of change it does not mean that the causes of changes are isomorphic to the actions implemented in the simulation. A computational model that is able to generate results similar to the available empirical evidence of a historical situation is necessary but not sufficient for explanation (Güner-Yanoff 2009). The level of abstraction of a model will depend on previous decisions about the scale use in the model, about what intends to explain and about the data available to compare the model predictions with what we can observe in the real world. The result is never a plurality of possible explanations, but a potentially very high number of degrees of freedom in any explanatory implicit decision. The decisions we make when accepting an explanation could be multiple and diverse.

It is important to recognize that, as a series of languages, rather than as a single technique, computer simulation can be used for different purposes and in a variety of theoretical frameworks. The use of artificial intelligence theories and techniques offers different advantages to scholars with a "post-modern" or hermeneutic idea of humanities. On the one hand it is important to mention the current trend on cognitive modeling and belief-desire-intention architectures for designing more "human-like" computer agents. It may help researchers in exploring non rational ways of decision making. On the other hand, the fact that a virtual past resides in a computer and it can be modified according to the needs of the human agent interacting with it contributes to change the traditional idea of the immutability of scientific theories. A computer program can be modified and altered at any time, and the consequences of modifications are immediately available to the user. Explanations appear to be as a result as flexible tools in the hands of people, used for anything the user need.

Is this a radically new way of understanding the past? In 2001, R. Hanson wrote: "We expect our descendants to run historical simulations for several different kinds of reasons. First, some historical simulations will be run for academic or intellectual interest, in order to learn more about what actually happened in the past, or about how history would have changed if conditions had changed. Other historical simulations, however, perhaps the vast majority, will be created for their story-telling and entertainment value" (Hanson 2001). Some interesting advances have already been made in this second aspect, in the use of virtual reality methods and simulated historical scenarios as a teaching tool in e-learning environments (Luch and Tamura 1999; Squire and Barab 2004; Allison 2008; Greengrass and Hughes 2008; Bogdanovych et al. 2012; Winnerling 2014; Smart et al. 2015; Telles and Alves 2015). Nevertheless, if we look at the actual impact of formal theories and computational tools and techniques in the domain of academic research, the results are slightly disappointing. They are not disappointing because "computing" has failed to do what it intended to do, which was to provide "history" with computerized tools and methods historians could use to expand the possibilities and to improve the quality of their research, but because most "historians" have failed to acknowledge many of the tools "computing" had come up with (Munro 2000; Boonstra et al. 2004). Within the humanities, computational modeling is infrequent at best, given the reticence of a significant portion of the humanistic community to technology, and the doubts [of many] as to whether the complex behavior of humans is even open to modelling through the reduction of our behavior to a few fundamental elements, that is to say, those that define us as human (Suarez and Sancho 2011).

Turchin (2008, 2011) considers there are two major reasons explaining this failure. First, computational simulation has been inspired directly by successes in physical sciences. Yet physicists traditionally chose to deal with systems and phenomena that are very different from those in history. Physicists tend to choose very simple systems with few interacting components (such as the solar system, the hydrogen atom, etc.) or with systems consisting of a huge number of identical components (as in the modynamics). As a result, very precise quantitative predictions can be made and empirically tested. But even in physical applications, such systems are rare, and in social sciences only very trivial questions can be reduced to such simplicity. Real societies always consist of many qualitatively and quantitatively different agents interacting in very complex ways. Furthermore, societies are not closed systems: they are strongly affected by exogenous forces, such as other human societies and by the physical world. Thus, it is not surprising that traditional physical approaches based on simple models should fail in historical applications. The second reason considered by Peter Turchin is that quantitative approaches typically employed by physicists require huge amounts of precisely measured data. For example, a physicist studying nonlinear laser dynamics would without further ado construct a highly controlled lab apparatus and proceed collecting hundreds of thousands of extremely accurate measurements. Then she or he will analyze these data with sophisticated methods on a high-powered computer. Nothing could be further from the reality encountered by a historical sociologist, who typically lacks data about many aspects of the historical system he is studying, while possessing fragmentary and approximate information about others. For example, one of the most important aspects of any society is just how many members it has. But even this kind of information usually must be reconstructed by historians on the basis of much guesswork.

If these two problems are the real reason why previous attempts failed, then some recent developments in natural sciences provide a basis for hope. First, during the last 20–30 years physicists and biologists have mounted a concerted attack on complex systems. A number of approaches can be cited here: nonlinear dynamics, synergetics, complexity, and so on. The use of powerful computers has been a key element in making these approaches work. Second, biologists, and ecologists in particular, have learned how to deal with short and noisy datasets. Again, plentiful computing power was a key enabler, allowing such computer-intensive approaches as nonlinear model fitting, bootstrapping, and cross-validation.

The main challenges for historical disciplines in operationalizing computational concepts in a science of long-term social dynamics is how can we systematically track and explain non-linear chains of causality that cascade from multi-scale inter-actions among individuals, groups, and the biophysical world up to the emergent level of social organization. This is especially difficult when traditional analyses and narratives are inherently linear and our knowledge of the past is static. Some equation-based models of human behavioral ecology and related approaches can account for non-linear dynamics (Levin et al. 2013; Anderies 2015). However, even these models have difficulty in adequately dealing with the kinds of multi-scale interactions of many spatially and culturally heterogeneous, independent actors. Furthermore, even with a firm understanding of the dynamics of human societies, how can we recognize and account for historical complex dynamics when key features are not preserved in the historical record? Meeting these challenges will require the development and application of robust theory about drivers and nature of long-term social change. Of course, it is impossible to carry out real-world experiments with past human systems—or even with modern ones at the scales of interest to most historians and archaeologists. Computational simulation modeling offers a valuable protocol for combining social theory and historical knowledge to create experimental environments in which to explore non-linear causality in complex systems and generate results that can be evaluated against the empirical historical data.

Therefore, we want to close this introduction to simulating the past theories, techniques and technologies remembering that the starting point of the explanation of prehistoric and ancient times by means of computer methods is not the creation of a particular artificial society that may reproduce what really happened in a remote past but the investigation of the mathematically possible development of specific classes of model systems (pure systems). As these pure systems usually generate a lot more different paths of development than are known from real human history, we should limit these possibilities by introducing constraints from well documented historical and ethnographical narratives or from archaeological data. The historically interesting question is then why these constraints appeared in reality. This approach can be traced back to Gibson's formulation of affordance theory (Gibson 1977, 1979). The relationship between successive historical events afforded by a potential causal factor can be termed an affordance. On this view, an event's historical function reflects the actions that may have been performed there and then by social agents, given both the particular situation (context) and the apparent directionality of the trajectory configured by previous events. In other words, the future state of a society is not predefined as a form of destiny, but there is a sense of directionality in the historical sequence of social actions with a dynamic, sometimes even adaptive, nature. Therefore, understanding those elements of the past that have been seen in the present assumes that the perceived strength of causes can be analyzed under the form of particular connections between the potential cause and the observed effect (Van Overwalle and Van Rooy 1998). In this way, we can understand that affordances are not properties, or at least not always properties (Chemero 2003). Affordances are relations between the abilities of people, their intentions, and what the concrete situation allow to be performed.

For this sort of "affordance-based" explanation be operative, the historian should discover what precipitating conditions generate an increase in the probability of the historical occurrence of an action at some place and moment and constrained by the social and environmental context. Beyond a simple addition of individual random decisions, what happened in the past should be defined in terms of social dispositions or capacities within a system of subjects, intentions, activities, actions and operations, some of them rational, others clearly indeterminate, impulsive or unconscious. The fact that the performance of some social action A, in circumstances T, had a probability P of having caused a change Y in some entity N (social agent, community of social agents or the nature itself), is a property of the social action A. It is a measurement of the intensity of the propensity, tendency, or inclination of certain events to appear in determined causal circumstances. In general, if the potentiality (occurring in a state S) to have state property X has led to a state S' where indeed X holds, then this state property X of state S' is called the fulfillment or actualization of the potentiality for X occurring in state S. A social action or sequence of social actions will be causally related with a state change if and only if the probability for the new state is higher in presence of that action that in its absence. Causal significance of a factor C for a factor E corresponds to the difference that the presence of C makes on E. That is, observed changes in the historical record of that particular event are not necessary determined univocally by the agent's will alone, but there is some probability that in some productive, distributive or use contexts, some values are more probable than others are. We are not suggesting that the cause is a probabilistic relationship, but it should be expressed probabilistically given the implicit uncertainty and the lack of any direct reference to what really happened there and then. In these circumstances, a historical situation should be defined as a relatively constant background condition consisting of possible stimuli afforded by the situation itself (the social agents and their environment). Thus, the primary explanandum of historical theory is social capacities: the capacity to work, to produce, to exchange, to interact, to obey, to impose something or someone. Social action appears as transformational processes to which social scientists attribute the achievement of some new state of the world: an end, goal, or result.

In any case, the purpose should be not to replicate the actual processes of historical change, but to obtain useful insights in terms of potentialities, dispositions or causal powers to construct a model to explain the long term social dynamics. Therefore, the starting point of the explanation of social systems by means of computer simulation is not the simulation of one particular system but the investigation of the mathematically possible development of specific classes of model systems (pure systems). As these pure systems usually generate a lot more different paths of development than are known from real human history, the automated archaeologist has to limit these possibilities by introducing known social constraints from social reality. The socially interesting question is then why these constraints appeared in reality. This particular procedure is aptly described by Bateson with the concept of "cybernetic explanation" (Bateson 1957).

We hope that a future society will very likely have the technological ability and the motivation to create large numbers of completely realistic social simulations. Simulated worlds created by such a future society to solve policy, strategic and research issues would most likely be retrospectives, i.e., historical simulations in which artificial intelligence would genuinely address human matters, rather than merely playing the role of a surrogate. These simulations will provide a rich source of information to a future society about how it arrived at its current stage of development as well as how it could avoid repeating the mistakes of the past. Someone has proposed that this future is very near, ca. 2050 (Jenkins 2006). We will rewrite this introduction in 35 years!

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