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From Behavioral Analysis to Prescription

1.1 Social Intelligence

The virtual reality (VR), augmented reality (AR), artificial intelligence (AI), 5G, mobile social media, block-chain, and other emerging technologies have been pushing the development of our society faster than ever. Since almost everyone plays a terminal in the huge network weaved by such techniques, we are driven to elevate our capacity of perception and information processing, to expand our scope of information access, and to speed up our interactions with other remote citizens. Assume that Lily planned to meet her client 10 miles away from her company. She was supposed to travel by subway for six stations and then by walk for about nine minutes for that face-to-face talk. However, due to the spread of the epidemic (like COVID-19) these days, the government has called on people to stay indoors as much as possible. Lily then arranged the talk online, which saved her one hour for commuting. The online video conference also brought her subsequent activities ahead of her original schedule so that she could have an additional social meeting with her friend Betty. This mundane but trivial example shows us that new technologies have drastically accelerated the social process nowadays. Such facilitation of information dissemination, together with its customized content, has greatly influenced the human society and, ultimately, results in a faster and more volatile emergence of social choices. Consequently, how to analyze the formation of social choices has become a central topic in the related research. And that is one of the primary questions of social intelligence: why and how the group intelligent behaviors could emerge. Accordingly, this basic question involves two levels – personal and social, which are sequentially focused in its two-phase history. In an early stage, psychological scholars first concerned with this field, treating social intelligence as a fundamental part of human intelligence. They referred it to the capacity to understand others according to your own similar experience in social contexts. Yet, in recent years, the tide has shifted to the focus on the intelligence of social collective behaviors

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as a whole, where the interactions within modern society are seamlessly connected.

Social intelligence was explicitly studied as early as the 1920s when Thorndike [1] postulated his framework of human intelligence by differentiating ideas, objects, and people that someone has to deal with. He did this in such a way that he could distinguish intelligence as academic, mechanical, and social dimensions. Social intelligence is further defined as "the ability to understand and manage men and women, boys and girls, and to act wisely in human relations." This basic idea clearly laid the foundation of the research scope and played as a guideline in later studies. Unlike the distinction between cognitive (understand others) and behavioral (act wisely in human relations) components from Thorndike, Vernon [2] defined social intelligence as "knowledge of social matters and insight into the moods or personality traits of strangers" (cognition) and as the ability to "get along with others and ease in society" (behavior). Different from the two definitions that involve both cognition and behavior, other studies mostly focus on one of them, such as "the ability to get along with others" for Moss and Hunt [3], "judge correctly the feelings, moods, and motivation of individuals" for Wedeck [4], "ability to judge people with respect to feelings, motives, thoughts, intentions, attitudes, and so on" for O'Sullivan et al. [5], and "individuals' fund of knowledge about the social world" for Cantor and Kihlstrom [6]. By summarizing, studies in the early stage tend to investigate one's ability to understand and interpret other people's psychological states and to interact with them for better emotional and mental supports.

Though some dispute might still exist in academic community, psychologists were mainly concerned about five cognitive aspects in traditional studies: social understanding, social memory, social perception, social creativity, and social knowledge. As a central part among all these facets, social understanding specifically refers to one's comprehension during social interaction with others. It requires individuals to interpret given surrounding social stimuli that are represented as the implications for the situation and their underlying features. The point is well illustrated by a sample test requirement: understand correctly what a person wants to express via verbal communications as well as nonverbal hints. Researches mostly concentrate on measurement methods such as George Washington Social Intelligence Test [7], Chapin Social Insight Test [8], the broad test batteries [9], and nonverbal decoding skills [10]. Social memory maintains both episodic and semantic memory contents with one's intention. Its performance is determined by the conscious recall of objectively and explicitly given a variously complex social circumstance. A representative study comes from Kosmitzki and John who discovered the factor for names and faces in laypersons' implicit theories [11]. Social perception, the ability to perceive social information in an agile way, could determine further information processing that is essential for social intelligence behaviors. Wong et al. selected several predesigned tasks to operationalize the measure of social perception [12]. Their experiments also involved interpretational demands that cannot be categorized into pure perceptual abilities. Analogous to the perceptual speed in models of academic intelligence, Carroll further specified the perceptual speed in social perception [13]. Social creativity, also called social flexibility, is the divergent production of individual's behavioral content. It is also reflected as the fluent production of possible interpretations of, or solutions for, a particular social situation. For quantitative evaluation, the participant's performance is not based on the correct answer but on the number of diversity of ideas [14]. This measure is able to successfully distinguish the domain of social cognitive flexibility from academic intellectual abilities. Social knowledge has been operationalized by the knowledge of good etiquette on the one hand, and by the social skills on the other hand. The latter is a concept similar to the taxonomy in AI, where knowledge is recognized as procedural and declarative parts according to its contents [15]. Procedural knowledge refers to the skills or tactics for specific tasks that could not be taught or recalled explicitly, whereas declarative knowledge reflects the world's facts and states and is stored in episodic and semantic memory. Social knowledge, in this sense, refers to the procedural part, which is distinct from social memory.

As alluded, social intelligence is defined at the micro individual level in the early stage. In particular, it investigates what cognitive facets together with their measurements support people's interaction to make themselves more popular. One of the best summaries might be Goleman's famous book which has been selling million copies worldwide [16]. In recent years, however, academic communities turned to analyze the collective social behavior as a whole. In this sense, social intelligence is redefined as the rational decision making that emerged from the whole society [17, 18]. Since the process stems from a bottom-up aggregation of social members' decisions, the macro emergent intelligence is also grounded on one's micro cognitions as well as behaviors. However, as most social members are self-interested and only have access to local information, their "myopic" decisions may not lead to the optimal choice overall. Thus, scholars concentrate on the modeling and analyzing social behavior by capturing individual social dynamics, the interaction between actual social and physical systems, and on the mechanism design that can guide the maximal utility of the society.

The new definition has endowed social intelligence with more comprehensive connotations, expanding such fields as an interdisciplinary research. For modeling and analyzing, studies involve individual behavior [19], social networks [20], or both of them [21]. Combined with the electronic commerce and mobile social media, user online behavior, commodity recommendation, social network evolution, social topic propagation, etc. are the most concerning issues.

For the interaction of social and physical systems, researchers have proposed Cyber-Physical-Social System (CPSS) as a promising direction [22]. Followed by such concept, related work on urban transportation [23], intelligent manufacturing [24], smart cities [25], block-chain [26], etc. have been conducted. We refer the reader to [27] for a detailed review. The mechanism design for an "optimal" social choice is originally from game theory, where each member is modeled as a "greedy" agent that maximizes his own utility. Yet with the increase of computational power and various social sensing technologies, agent-based social computing is introduced for complex problems. For instance, social trust mechanism [28], incentive design [29], and supply chain [30] are main areas of applications.

1.2 Human–Machine Interaction

Not only in social management but also similar things happened in the area of human–machine interaction (HMI). On the one hand, new technologies have endowed rigid machines with higher level of autonomy and intelligence. This undoubtedly releases human labor force from trivial and tedious work. On the other hand, technologies have also fiercely promoted the complexity of systems where several human operators participate to jointly undertake complicated tasks with "smart" machines. Representative cases come from the manipulation of aerospace craft, surveillance of nuclear power plant, control of high-speed railway, driving of intelligent vehicles, etc. In particular scenarios, these real-time human-in-loop systems (can be viewed as a small-scaled CPSS as well) usually involve fast exchange of information or control instructions between machines and operators. For instance, manual rendezvous and docking of spacecraft is still retained as an alternative for emergent situations, though the automated way has become sufficiently mature. Manual rendezvous process, often lasting for several hours, requires operator to constantly monitor the current position of spacecraft and fine tune its attitude for accurate alignment. Such a long period of concentration may probably lead to a cognitive fatigue for human individual and thus a decrease of his perception ability. In addition, cognitive fatigue and cognitive overload may also stem from inappropriate task allocation [31]. They are very likely to result in the inconsistency of HMI that causes human–machine conflicts. Predictably, such incompatible coordination of human–machines will lead to the failure of the task, even with multiple sorts of safety accidents [32, 33].

In essence, the fundamental reason for potential human–machine conflicts is that traditional design paradigm internalizes operators as a part of the system and strictly regulates their operations according to the predetermined operational rules or instructions. This design principle mainly characterizes coarse requirements of human operator and assumes that they can "perfectly" undertake their assigned subtasks. Yet by contrast, different operators have different physiological and psychological foundations such as cognitive load, distraction, and knowledge level. The distinct cognitive status may result in different decision-making styles, or even unsafe operations [34]. To avoid such potential conflicts, researchers have been focusing on many promising directions, one of which is the adaptive or adaptable automation [35]. The main goal is to develop an adaptive mechanism that is capable of dynamic allocation of suitable tasks/functions to both humans and machines so that their incompatibility is reduced to a minimum level. For this goal, it is necessary to establish a reliable model for a human operator to investigate his operational style, preference, or possible errors. As the dynamic allocation usually takes place during fast interaction, the computational model seems appropriate. It can fully exploit the elevation of computing power from contemporary hardware. Moreover, due to the difference and time-variant cognitive status of individuals, the model needs to monitor and "learn" the operator's physiological and mental states (like the fatigue or risk preference) from his constant interactions, and further prescribe his actions to avoid human errors.

Yet how to provide a customized prescription to a specific operator? Solutions may come from the conquering of heterogeneity in complex systems. As alluded before, traditional design paradigm deems participated human operator as a system "component" and regulates him via deterministic rules and instructions. It neglects individual's heterogeneity. Unlike the complex social system where heterogeneity usually refers to individual behavioral patterns, it concentrates more on the diversity in cognition and deliberation of different people (which are complex biological systems). Such diversity is our intrinsic characteristic and, in turn, drives our civilization forward. As indicated by Prof. Marvin Minsky, a father of Artificial Intelligence, it is vast individual diversity that causes the emergence of intelligence [36, 37]. One important source of the cognitive heterogeneity lies in the different mental beliefs of the world. It can ultimately result in the emergent dynamics of human–machine system (from same initial states and operational rules), sometimes chaotic, sometimes oscillating, and sometimes in a nice order. Description, analysis, and even prescription of such cognitive heterogeneity demand distinct computational models or, at least, distinct parameter levels. Classic psychology conforms to the "Experiment—Induction—Modeling—Validation" modeling path. However, this may not be applicable again for highly time-variant systems. On the one hand, subjects in psychological or neural biological experiments usually account for quite a small part of the whole studied group. This often brings sampling bias, leading to the inaccurate cognitive models that do not reflect behavioral differences among individuals. On the other hand, the final cognitive models from traditional approach are "static." They can hardly model the dynamic cognitive process: human's reasoning and decision-making patterns may evolve as his knowledge and skills gradually accumulates (such accumulation usually comes from his learning, imitation, socialization, etc.). Therefore, to analyze and prescribe one's heterogeneous behavior, new paradigm of cognitive modeling is required to simulate various possible actions or responses to investigate potential errors and safety problems, especially in different interactive environments.

1.3 From Behavior Analysis to Prescription

The broader definition of social intelligence and new challenges faced by HMI have linked the promising fine-grained human behavioral research with several related traditional studies, such as game theory, mechanism design, complex networks, and so on. Yet, it does not mean that the specific area is reinventing wheels. Admittedly, game theory and mechanism design – perhaps the most representative methodologies from those studies – have provided us a strict prototype to analyze distributed systems from the perspectives of agent's optimal strategy selection and exogenous rule making. But when it comes to the real system, things could be worse. On the one hand, even a local part of the human group involves multiple participants, and the complicated dynamics among all these components are usually not able to be analytically modeled. For those clearly established game or mechanism models (if it has), they usually include too many decision factors that are sensitive to initial conditions and highly inter-dependent. Consequently, analysis by equilibrium computation for a large-scale population seems impossible in practice. On the other hand, members in a system are inclined to be "bounded rational." That is, given a specific circumstance, they tend to choose an "acceptable" strategy rather than the "optimal" one, without comparing every candidate's response accurately. Such phenomenon may not be strictly explained by the game model.

Limitations from all these aspects have brought the research on social and human–machine hybrid systems to the bottom-up methodology where the group behaviors, as mentioned before, are "grown" from individuals. The virtual individuals are usually called agents that react to their surrounding environment signals according to their predefined rules. Such a multiagent paradigm is adopted by comprehensive studies ranging from computational social science [38], computational economics [39], urban transportation analysis [40, 41], contagious disease propagation [42], to recent anticrime and terrorism [43]. By contrast with other components, agent-based individual/population plays the central part of those computational systems. Clearly, it is the aggregation of each individual's behavior (represented as agent's behavior in simulation) that determines the whole system's dynamics and thus distinguishes different systemic evolutionary paths. Yet unlike the environmental elements (vehicles and traffic infrastructure in urban transportation, for example) where many analytical or numerical models can be exploited, agent behavioral models are much more difficult to establish. This is because our behaviors in real hybrid system are subjective and uncertain. We have not recognized ourselves quite well. Therefore, the indispensable task of how to build "accurate" and reasonable computational models of human behaviors receives constant research from various disciplines.

Traditionally, human behavior is viewed as a result of decision making. And three approaches are used to model the decision-making process. The first type is simple stochastic sampling. In this approach, human decision making is deemed as a selection process among several behavioral candidates. For instance, the migration behavior is modeled as a binary variable and a selection for potential destination cities if the variable gets "True." The selection result is determined by the sampling probability from a particular distribution (such as the uniform distribution) [44]. The second type considers decision making as optimization and uses greedy methods to simulate such process. In practice, agent's selected behavior comes from the maximization of his expected utility function. To model different goals from different groups of individuals, various types of utility functions are introduced in particular scenarios. For instance, in travel mode selection, users usually concentrate on the travel time, travel cost, familiarity of the route, etc. Thus, agents may choose to maximize one of them when they are contradictory with each other. Utility maximization is mainly adopted by the computational economics like disaggregate selection model [45, 46], game theory [47], to name a few. The third type of decision making comes from AI (called the production rule systems), which uses "If…Then…" rules to model individual selections. In such an implementation, agent's external perception signal is mapped as the rule's condition (the "If …" part), while the corresponding behavior is mapped as the rule's conclusion (the "Then …" part). Different rules may have identical conditions but different conclusions, so that same input signals are able to fire multiple rules. To avoid multiple behaviors, conflict resolution mechanisms must be introduced [48–50]. A typical mechanism is to assign each rule with a preference degree. Then all the fired rules are ranked according to their preferences, and the candidate with top preference is adopted as his final action. This operation, in essence, can be also viewed as a utility maximization, leaving that utility function implicitly defined as the preference quantitatively. Generally, simple stochastic sampling and greedy methods are easy to implement. Yet they have not considered human reasoning process. The production rule systems mapped the environment input to a specific action. It treats the reasoning as a "black box." Such myopic one-step behavior is weak to simulate real human activities.

Though computationally simple, the utility function and "black" decision process have brought us some obvious dilemmas for real applications.

First, "black box" model severely depends on the training data, while the reasons behind the final decisions are not understandable. Researchers are not able to dig into social phenomena to analyze how the specific individual as well as group behavior is formed and propagates. It is this vagueness that leads to large deviations between real social systems and simulation results. Thus, computational experiments for management policies grounded on such agent behaviors seem not convincing. Second, modern complexity and computational social science not only require the traceable analysis of existing dynamics but also expect further "soft" management for the human society by prescribing individual behaviors, so as to ease social conflicts from various groups. In the environment of free market, only by clearly understanding people's thinking and decision making can we fundamentally guide their expectations and ultimately exert influence on their behavior patterns.

Both of the above dilemmas have motivated us to conduct a constant research that is contained in this book. More essentially, the granularity of current main behavioral models does not support the agent's endogenous deliberation. We need models at a finer level. To achieve such a goal, however, we are facing great challenges. One difficulty comes from the high heterogeneity of actual social system that extremely stochastic individual behaviors are not represented by a universal model. It makes us develop specific models for each type of social members. Such modeling approach is not operational since there are numerous behavioral patterns in reality. A second difficulty lies in the huge search space when each type of agent behavioral models available. As the number of model variables increases, the combinations of different decision rules form a huge reasoning space. Searching for a "plausible" reasoning path in such a huge space is computationally non-deterministic polynomial hard (NP hard). And effective strategies need to be developed to overcome the challenges.

Situations are not that bad. Recent breakthroughs in AI have ignited our inspiration. For the high heterogeneity of different social individuals, a potential solution to build corresponding virtual agents might be using machine learning techniques. Specifically, a few general behavioral templates can be constructed at first, and interactive learning can be introduced based on a particular template to imitate the detailed behavioral dynamics of its related actual user host [51, 52]. The long-term interaction and imitation will adaptively fine-tune the general agent model, capturing one's specific decision patterns automatically. By that way, building thousands of heterogeneous agent models can be avoided. For the huge reasoning space, Alpha Go from DeepMind may provide a feasible direction [53, 54]. Given the environment and agent internal states, the system's evolutionary paths are self-computed via cooperation and games among agent groups. The evolution will autonomously explore certain decision sequences with high probabilities in the reasoning space. And reinforcement learning could also be exploited to iteratively update the probability of each action. By doing this, we are able to prune the "impossible" system evolutionary paths so that the NP-hard computation could be conducted within an acceptable time.

1.4 Parallel Population and Parallel Human

Breakthroughs from AI have directly led to the work in this book, that is, the AI-based parallel population/parallel people for behavioral prescription. The overall structure of the system is a tiered (or nested) bi-closed loop, as illustrated in Figure 1.1. We will explain its details in two levels. For social management, the outer two loops establish a parallel population system which consists of the real population and its virtual counterpart – artificial population (represented as real and artificial "Environment, Population System, System Metrics," respectively). Including virtual individuals as well as their social relationships (like family, friends, schoolmates, and colleagues), artificial population plays the virtual society that is a digital mapping of the reality. As two autonomous systems, artificial and real populations keep running independently for self-evolution. At the same time, they have also formed an interactive setting to prescribe real

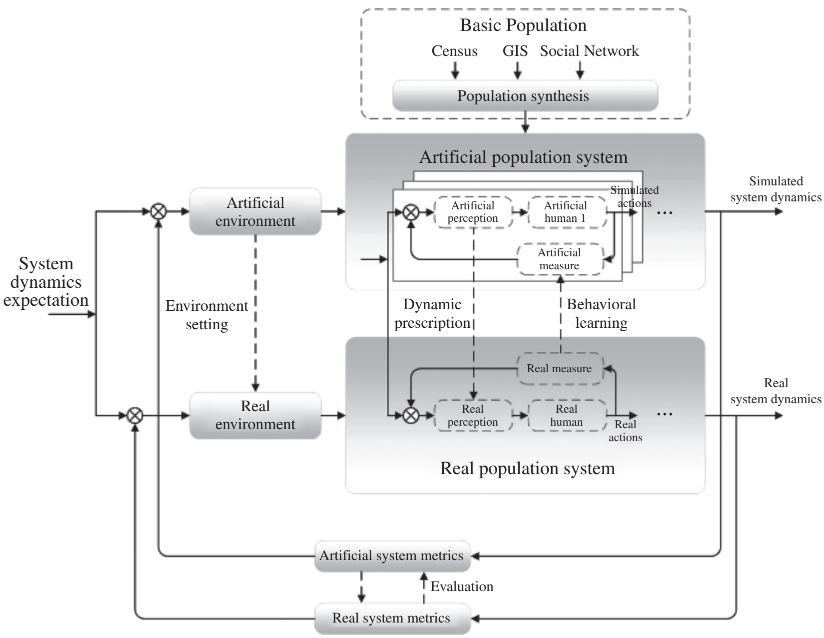

Figure 1.1 Structure of parallel population and parallel human systems.

system's evolutionary trajectories in a macro scope. Such prescription relies on the comparative evaluation between the two systems' running dynamics and on the active environment setting from artificial to real ones. The building of artificial population starts from a basic population synthesis, which provides initial individual states with social network patterns. For a clear organization, this part is separately drawn in the figure and will be discussed later.

As system dynamics are aggregations of multiple individuals, it is natural to decompose the behavioral prescription into a micro level where a group of artificial individuals are developed for a particular real individual. The real individual with its virtual counterparts constitutes a many-to-one parallel human system (the inner two closed loops in Figure 1.1), with every artificial individual standing for a probable representative evolutionary state. Similar to a parallel population, local control for each real–artificial human runs independently in an autonomous way. And their constant interaction will dynamically describe, predict, and prescribe one's specific actions based on sufficient computational experiments by the artificial groups. In particular, the interaction involves behavioral learning from real to artificial individual, to adaptively calibrate the digital human model, and dynamic prescription from artificial to real individual, to adjust the actual perception signal as expected. In the implementation, AI-based agent technology is a suitable path for the modeling and computation of parallel human.

Although the parallel population shows a nested structure, it should be noted that the outer two peer closed loops can be tailored and simplified when it is not applied for the smart management of complex social systems. This is determined by the specific task that the system aims to complete. For example, in a scenario of spacecraft manipulation concerning multiple human operators, there are no complicated social network patterns as real social systems. Artificial population system, at this time, degenerates into only a few agents. When such a process involves only one operator, artificial population system vanishes, leaving only one parallel human loop. Note that the machines are implicitly contained in the control loops and not illustrated in the figure. It is because the modeling for humans is far more complex than that for machines, and our focus lies much more on the human analysis as well.

In contrast with traditional analytical models, individual models for a specific person can sufficiently investigate various possible evolutionary states as well as his responded actions. This is proved to be effective for individual heterogeneity in the science of complexity. More deeply, such individual heterogeneity derives from differences in personal cognition, which we call it mental heterogeneity. Therefore, the ultimate goal of parallel human (with its aggregation – parallel people) is to computationally model and simulate mental heterogeneity. We will investigate this problem from AI and cognitive computing later in this book.

1.5 Central Themes and Structure of this Book

As alluded before, the central theme of this book concentrates on how to computationally model a human individual's deliberation and thinking, so that his behavior is prescribed to achieve the system's expected control objective. Our discussion will address the basic theory and methodology for modeling as well as some implementation techniques. Potential acceleration technologies will be also exploited in our prototype system due to the high computational cost. Some application cases from different fields are also contained to show preliminary validations. The overall organization of the book is shown in Figure 1.2. Though Chapter 8 may be concerned about with implementations, we generally follow the technological path rather than system components to introduce our work. Our discussion begins with the synthesis of basic population (as shown in

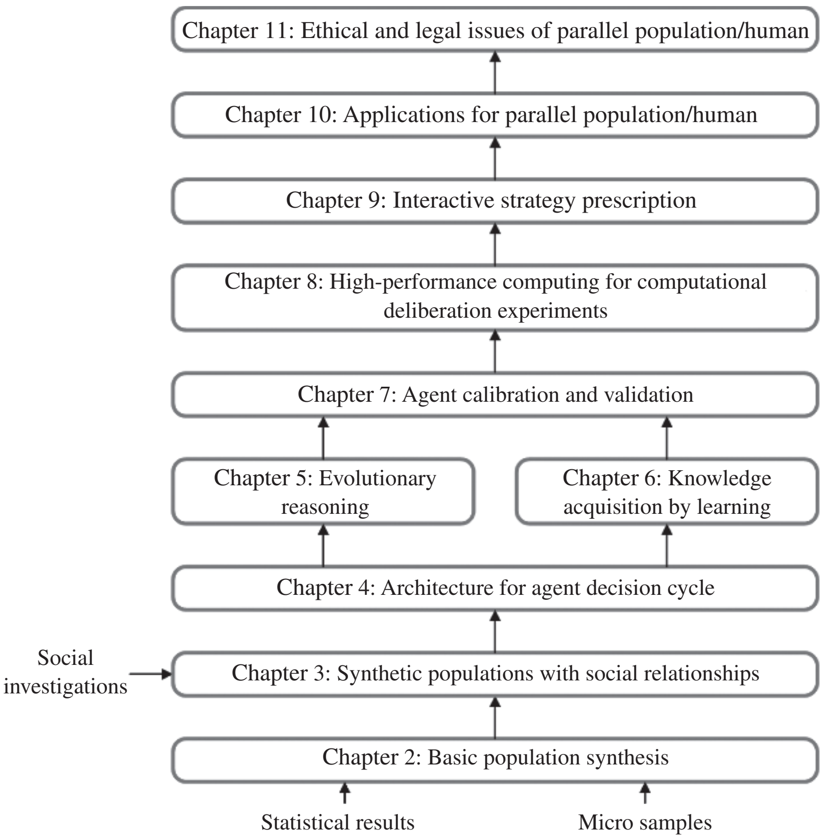

Figure 1.2 Organization of this book.

the upper dashed box in Figure 1.1), which includes Chapters 2 and 3. These two progressive chapters elucidate how to generate a "static" set of virtual individuals with their personal attributes and mutual social relationships according to statistical results and optional micro samples. Chapter 2 only considers the individuals, while Chapter 3 further addresses social organizations. The achieved basic population plays a start state in the subsequent artificial population evolution. Next, we move to the micro level, concentrating on the individual cognition and behavioral modeling. This part includes four chapters, Chapters 4–7. Generally, the central problem for such an issue lies in three intercoupling aspects: the representation of human knowledge, the acquisition of an individual's knowledge in a static/dynamic way, and the exploitation of one's knowledge to elicit a specific decision/action. These three aspects are also fundamental questions in human-like intelligence. Chapter 4 talks about the cognitive architecture for agent decision cycle. It provides a unified container or framework that organizes knowledge segments and data flow in decision process. On the basis of such framework, Chapters 5 and 6 address the learning and reasoning, which provide rudimentary solutions for knowledge acquisition and application. To model the mental heterogeneity in a time-variant human-in-loop environment specifically, we put our emphasis on adaptive learning through detected individual actions. The decision making based on reasoning via one's knowledge base adopts an evolutionary paradigm rather than classic reasoning in AI research. This is in line with the philosophy from science of complexity and cognition where the deliberation results from a bottom-up emergence. We do not give a separate chapter to the knowledge representation because existing relevant techniques are directly exploited. A brief introduction is included in Chapter 5. Interested readers can easily find corresponding details in other related literature. The last but not least problem for artificial human modeling is the parameter calibration and validation, which is essential for the reliable use of models. For a large-scale social system in particular, model calibration seems more important, since compared with a few agents, parameter values in such systems are difficult to be fully measured in a wide range. This sampling bias may cause the achieved parameters not representative enough and thus impacts the accuracy of the model. Several calibration methods will be presented in Chapter 7, trying to avoid such a dilemma. After establishing learning and reasoning mechanisms for artificial human, we next turn to their implementation. In Chapters 8 and 9, we consider acceleration approaches for a large-scale knowledge base that is computationally expensive. It is almost inevitable in practice since one's mental repository is usually complicated. Distributed reasoning and active strategy prescription via cloud computing are elucidated. Some theoretical foundations on the completeness and optimality in such a reasoning mode are also analyzed in these two chapters. The book concludes with some applications in Chapter 10, ranging from computational demography to urban transportation management and control, to evacuation in emergency. Some ethical and legal issues of parallel population/human are further discussed in Chapter 11.

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