TiDEC: A Two-Layered Integrated Decision Cycle for Population Evolution

Peijun Ye , Xiao Wang, Gang Xiong , Shichao Chen, and Fei-Yue Wang

Abstract—Agent-based simulation is a useful approach for the analysis of dynamic population evolution. In this field, the existing models mostly treat the migration behavior as a result of utility maximization, which partially ignores the endogenous mechanisms of human decision making. To simulate such a process, this article proposes a new cognitive architecture called the two-layered integrated decision cycle (TiDEC) which characterizes the individual's decision-making process. Different from the previous ones, the new hybrid architecture incorporates deep neural networks for its perception and implicit knowledge learning. The proposed model is applied in China and U.S. population evolution. To the best of our knowledge, this is the first time that the cognitive computation is used in such a field. Computational experiments using the actual census data indicate that the cognitive model, compared with the traditional utility maximization methods, cannot only reconstruct the historical demographic features but also achieve better prediction of future evolutionary dynamics.

Index Terms—Agent-based model (ABM), cognitive architecture, population evolution.

I. INTRODUCTION

THE ADVENT of agent-based modeling provides demographic researchers and urban planners with an advanced analysis tool to investigate the dynamic population distributions in an alternative way. This kind of model usually grows emergent features at the systemic level by interacting heterogeneous agents with their neighbors and local surrounding environments. Since its emergence, various studies have been conducting constantly, ranging from general methodology [1], specific techniques [2], [3], to concrete applications [4], [5]. Among the applications, social population evolution is an important field that has attracted research focus in recent years [6]–[8].

Overall, population simulation involves two major steps, namely, 1) population synthesis and 2) dynamic evolution. The first step aims to generate a population baseline that statistically matches the reality for the studied area. Such a problem can be modeled as a multiobjective or multidimensional optimization, and can be effectively solved by the classic methods [9]–[11]. The synthetic population can be used as an initial state of the system and plays a start point of the subsequent simulation. The second step, dynamic evolution, builds an agent model on each individual, defines computational models of environment that the agents embedded, and evolves the system for a certain period of time. Different agent and environment models have been used in different application fields, such as distributed control [12], [13]; social game and cooperation [14], [15]; transportation simulation [16], [17]; and social cognition [18]. For computational demography, research mostly focuses on fertility, mortality, and migration. Given an initial state, these three aspects sufficiently determine the population features like the density, age structure, and spatial distribution. Compared with the other two, migration has attracted most studies up to now. This might result from that fertility and mortality rates are usually available from population investigation. The existing migration models mostly trigger agent's behavior by maximizing their utilities (also called pay-off in some scenarios) function or simply by calculating the intensity of a social force. As shown in the next section, such utility maximization usually endows the potential destination with a subjective utility and simplifies one's decision process as the utility computation. This operation is reasonable to some extent for its relatively low computational complexity. However, it also treats the human decision as a "black box" and ignores the fact that decision making is a high-level cognitive process based on the basic cognitive functions like memory, reasoning, and learning. Therefore, grounding the agent-based model (ABM) at a more fine-grained level might grasp the essence of the human decision making in a plausible way and ultimately bring a comprehensive predictability to the simulation. With such motivation, this article attempts to endogenously characterize the human decision-making process in population evolution via cognitive

computation. To the best of our knowledge, the contribution of this article is two-fold.

1) A general cognitive architecture that simulates the human decision-making process is proposed. Different from the existing ones, the hybrid architecture, called two-layered integrated decision cycle (TiDEC), introduces deep neural networks (DNNs), which are able to simulate the uncertainty of human perception. The architecture also enables researchers to concentrate on domain knowledge in ABM development rather than the modeling of decision making.

2) The proposed TiDEC architecture is applied in agent-based population evolution. This is the first time that cognitive computation is introduced into such an area. Compared with the traditional models, the cognitive-based method is more fined-grained and is expected to have a better generalization performance. To test and validate our model, computational experiments based on Chinese and U.S. census data are conducted. The results indicate that the cognitive model, compared with the traditional utility maximization, cannot only reconstruct historical demographic features but also achieve a better prediction of future evolutionary dynamics.

This article consists of six sections. After the introduction, in Section II, we review several main kinds of cognitive architectures as well as agent-based migration models, and give their potential pros and cons according to our previous study. Section III elucidates the proposed TiDEC model in an overview. By considering four decision factors, Section IV shows the model implementation in population evolution. Section V describes the data source of the Chinese and U.S. population with model calibration. Then, computational experiments are analyzed qualitatively and quantitatively. This article is concluded in Section VI with some additional discussions about the future work.

II. RELATED WORK

A. Cognitive Architecture

Basically, the mainstreams of cognitive architectures can be categorized into two types, namely, symbolic and emergent. The symbolic systems usually store the agent knowledge as a group of formal logic rules and maintain a consistent knowledge base (KB) within each agent. The reasoning process is modeled as a sensation-decision-actuation cycle, which is iteratively conducted throughout the computation. The symbolic systems distinguish basic cognitive functions and construct their work flows in deliberation. Representatives are adaptive control of thought-rational (ACT-R) [19], state, operator, and result (SOAR) [20], etc. Except a few general models, most symbolic systems concentrate on a minority of cognitive modules and aim to complete specific tasks like robot control or problem solving [21], [22]. In contrast, the emergent architectures are on the basis of the biological structure of the brain. They try to "reproduce" the human cognition from bottom up by simulating the cortex and neuron activities. The emergent architectures typically adopt hierarchical structures where the basic cognitions for different aspects concurrently take place at the bottom level and then the knowledge

is refined at the top. Representatives of this type involve hierarchical temporal memory (HTM) [23], Leabra [24], etc. The emergent architectures are mainly used in pattern recognition in computer vision or natural language processing. There are also a few architectures that attempt to combine the two types, such as the connectionist learning with adaptive rule induction online (CLARION) [25]. However, these models characterize the cognitive process at a very coarse level. For instance, CLARION uses four subsystems—action-centered subsystem, nonaction-centered subsystem, motivational subsystem, and meta-cognitive subsystem—to describe the cognition. Such design lacks a strong representation of the decision making, which motivates the work of this article. For a more detailed review on cognitive architecture, the readers are suggested to refer to [26].

B. Agent-Based Migration Model

Different from the traditional approaches where migration flow is aggregated as the outcome of both push social force of origin and pull social force of destination [27], ABM (re)produces endogenous decisions by interacting individuals with heterogeneous characteristics and idiosyncrasies. Up to date, ABM might be the only method that allows for explicit modeling of social interactions in multiple social networks. Such advantage nourishes constant research about how the migration takes place. To the best of our knowledge, there are four main types of ABMs for population migration.

The first type is the minimalist model, appeared as early in 1969, where migration takes place when the number of neighbors in different race exceeds a predefined threshold. This is the so-called Schelling's segregation model [28]. Saadi et al. [29] maximized agent's utility under particular equilibrium conditions. They focus on urban–rural migration flow. Similar utility maximization is also used in Jiang's model [30]. Ichinose et al. [31] introduced the game theory to analyze long-range migration. His model considers the cooperation in groups during migration. The second type comes from microeconomic domain. Heiland links the migration with economic foundations without interaction [32]. Employment status and location are considered to maximize expected utility. Biondo et al. [33] further considered return migration flow. In his study, personal income and social capital both determine the time span of an agent's dwelling. Rehm [34] used multinomial logit, a classic formula for disaggregate choice in economics, to model the migration behavior. The third type concentrates on social psychology. Reichlova [35] presented a hierarchical migration model using the theory of Maslow need, where agent's migration relies on safety, income, and social needs. Kniveton et al. [36] and Smith [37] conducted studies about population migration under climate changes in some African countries. The fourth type of models achieves migration behavior by heuristics. Rogers et al. [38] studied the migration with social-economic inequality. In his study, migration is more inclined to occur when the accessible resources fall below a certain threshold. Hafizoglu and Sen [39] simulated migration behavior in geographically distributed communities. Agents with binary and continuous states may either adopt the dominant state of their community or migrate to
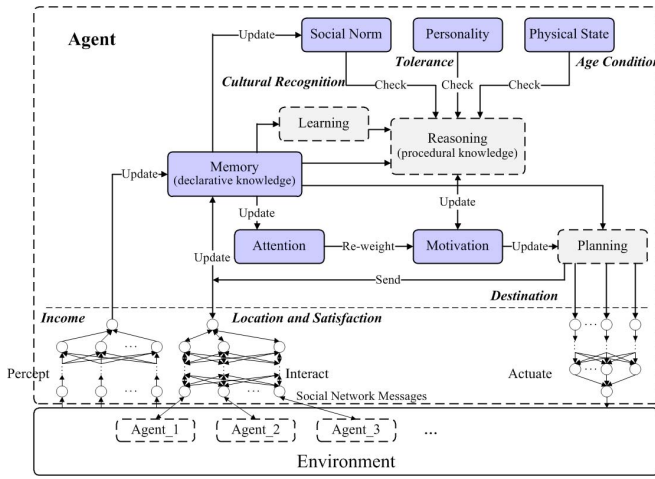
Fig. 1. TiDEC.

others that are more consistent with them. As mentioned in the previous section, the four types of ABMs are relatively weak to reflect a general decision-making process. As such, we attempt to introduce the cognitive cycle to simulate the migration behavior at a more fine-grained level.

III. TWO-LAYERED INTEGRATED DECISION CYCLE

To simulate the whole process of human decision making, we propose a cognitive model called TiDEC. As shown in Fig. 1, the model is a hybrid structure and intended to capture all the essential cognitive elements. At the bottom is a DNN layer which represents the agent's biological sensory and motor systems. The perception DNN (proactively or passively) receives the low-level sensory signals from the environment and converts them into symbolic concepts or numerical values for the high-level deliberative system. In particular, the agent's concept space can be modeled as a set of <entity, attribute, value> tuples. The perception DNN uses the environment state features as its input vector and outputs the value of each attribute. For specific scenarios, the attribute values can be either symbolic or numerical.

The actuation DNN controls the agent's actuators according to the input parameters provided by the deliberative results. The interaction DNN plays a similar function and they can be integrated into the perception and actuation according to the signal-flow directions. Here, we distinguish them in the sense of functionality. To represent uncertainty, the DNN may endow some percept attributes with probabilistic values. Such results are provided to the upper-level system for further reasoning. The perception, actuation, and learning parameters are affected by the agent's physical state, such as age and certain disease.

The top layer of the cognitive model is a probabilistic symbolic system, which simulates human logic or numerical reasoning and learning. This high-level system attempts to reflect the deliberative process of the brain. Based on multiple inputs (with their probability) from the bottom layer, the memory stores uncertain facts about the world as well as about himself. This part is also called the declarative knowledge. By comparing current environment state and historical

knowledge, particular learning algorithms such as *Q*-learning can be conducted. The reasoning module keeps procedural knowledge which is mainly composed of rules. Further reasoning will be proactively performed based on memory to generate extended facts. It is the most important process of deliberation and is affected by social norm, personality, and physical state. The reasoning will update the motivations that represent the agent's desires in several aspects. The motivations are sorted in different priority by attention to satisfy the most urgent needs. Starting from current declarative memory, the motivation with highest priority will be decomposed in planning and generate a series of actions. These actions will be maintained until the corresponding motivation is fulfilled or canceled. Each action is executed by sending the related control objectives to the actuation DNN.

IV. POPULATION EVOLUTION USING TiDEC

In this section, the proposed TiDEC model is used in population evolution. Different from the traditional models, the agent's behavior is deemed as a perception–reasoning–planning–actuation loop. This loop is conducted throughout the agent's "life." For simplicity, we ignore the immigration and emigration abroad and only consider fertility, mortality, and domestic migration across cities. We select four significant decision factors, which are personal income, family attraction, registration, and ethnic group. Social network is also considered in both of the migration and matrimony (thus impacts the fertility).

A. Perception, Interaction and Actuation

The first stage of the agent's decision cycle is to observe and retrieve information from environment (perception) and social networks (interaction). In our migration scenario, this is implemented via a three-layered neural network, using the four decision factors mentioned before as its inputs. For personal attributes, agent income and residential place are detected. Personal income is stochastically determined according to the local economic level of the city. Only employed agents have such input. The residential place will be sent to memory for further processing. For social network interaction, the agent will record the locations of his family members. He will also record the personal income, registration places, and the ethnic groups of his friends. These facts are sent to memory to update the agent's belief. The actuation network here is simplified as essential program operations that facilitate the simulation, such as the exit from the original area when migrated.

B. Memory

Memory contains the observed results directly from perception and interaction. Basically, there are two kinds of declarative knowledge. One is variable knowledge like the personal and other agents' locations or incomes. They are typically stored as tuples like $<agent_i, attr_i, value_i>$ which represents the agent ID, the ith attribute's name, and value, respectively. Note that the attributes may have symbolic values. The other is permanent cognition such as the geographical knowledge. This information is encoded as a mental map
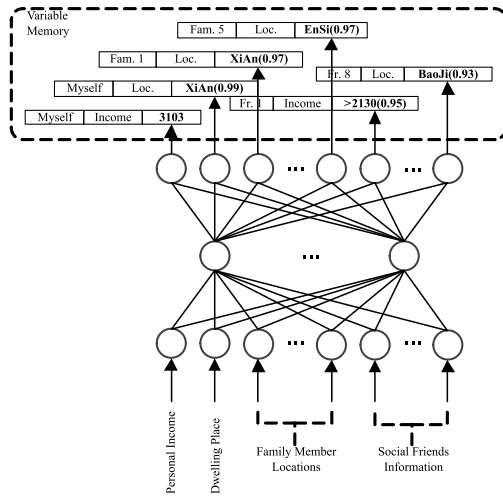
Fig. 2. Memory update process.

representing temporal, spatial, or other relationships among interested objects.

The process of perception and memory update is illustrated in Fig. 2. Each piece of knowledge in the variable memory contains a probability (shown in the brackets) for a particular attribute value. The probability is updated in every training iteration, through the perception DNN. In an online case, such an update takes place in every simulation step via online learning. Note that for simplicity, Fig. 2 only gives one value-probability pair for each attribute, while in implementation, the attribute usually involves several values and each value corresponds to a probabilistic weigh that the DNN will calculate. Fig. 2 also omits the normalization of the probability, which is a usual operation in DNN via a softmax function. Note that memory does not necessarily reflect the reality. It may include incorrect beliefs represented by a wrong probability here. Nevertheless, the agent will treat these beliefs as correct ones from his point of view and make decisions based on them.

The introduction of DNN can simulate the uncertainty of individual perceptions from person to person, provided that different individual samples are used to train the network. However, limited by the computational resources, creating a DNN for each agent is feasible only in the scenarios with a few agents. For a certain number of participants, a common network may be an alternative way for the implementation. Fig. 3 shows the structure of the system, in which each agent sends his surrounded social and environmental signals to the DNN and receives the probabilistic symbolic representations as his perception. Such aggregated form will not sacrifice the heterogeneity of agents, since the DNN is able to distinct different individual perceptions via corresponding training data. Note that in the figure, we only draw the perception network. The actuation network can be analogously designed.

C. Social Norm, Personality and Physical State

The three functions represent the agent's endogenous states. Social norm, enforced by the society or organization, refers to the regulations or customs that the agent needs to comply
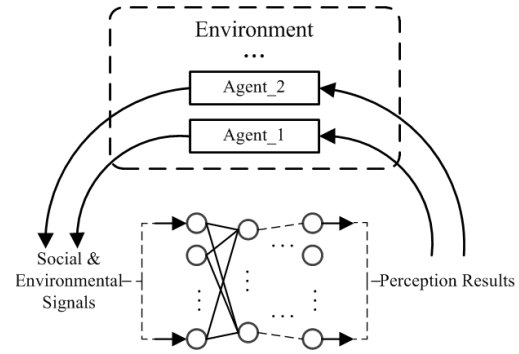

Fig. 3. Common DNN in the implementation.

with. They are not mandatory. But the agent will be punished (such as be isolated by others) if he violates them. In our application, the agent prefers to dwell in his registered place, since it may probably bring him much inconvenience if he does not have local registration (such as limitations to purchase a house, or limitations to enroll the nearest school for his child). In addition, for minor ethnic groups, agent is inclined to live in the place where the same ethnic group is prevalent. This social norm stems from the cultural recognition and has already been proved by Schelling's model [28]. The satisfaction from registration is quantified as

$$SI_{reg} = \begin{cases} 1 & \text{If agent has a local reg} \\ \frac{k}{\text{dist}(\text{ResCity},\text{RegCity})} & \text{otherwise} \end{cases} \quad (1)$$

where dist means the distance between the agent's residential place and registration place. k is a constant that keeps $(k/[\text{dist}(\text{ResCity}, \text{RegCity})]) \leq 1$. To avoid the break point, we set

$$k = \min_{\text{ResCity} \neq \text{RegCity}} \text{dist}(\text{ResCity}, \text{RegCity}).$$

To calculate the satisfaction from the ethnic group, we rank the cities with the proportion of each minor group in descending order according to the census data. The satisfaction for minorities is computed as

$$SI_{eth} = 1 - \frac{\#<\text{ResCity}>}{|<\text{City}>|} \quad (2)$$

where # means the sequential index of the residential city and $|\cdot|$ means the total number of cities. Personality characterizes one's behavioral style or pattern. Radical people are less tolerant of dissatisfaction, and thus more possible to migrate. In contrast, the conservative share high thresholds for dissatisfaction and more adaptive to the current situation. In particular, we set three types of personalities, radical, medium, and conservative. They are distinguished via a tolerance variable. Physical state stores the agent's physical conditions and social attributes, including his age, gender, current city, etc. These three cognitive functions may vary from person to person. Different norms/types/states as well as different parameters will lead to different decision styles. Therefore, they are the sources of heterogeneity among agents.

D. Reasoning

Reasoning plays the most central role in the decision making. It is based on the facts in memory, and also supported

by a specific kind of knowledge called procedural knowledge. The basic procedural knowledge in population migration is that if the agent dissatisfies the current situation, then he will migrate to another place. The satisfaction is influenced by social norm, personality and physical state, and its computation concentrates on four interested aspects. The first is personal income, determined by the local economic conditions. Employed agent will receive a particular amount of pay-offs (perceived and recorded in his memory), and compare his income with his friends (perceived from his social networks). If this metric is lower (higher) than the average level, he will become unsatisfied (satisfied) in the economic aspect. The greater the deviation between the two values, the more unsatisfied (or satisfied) he is. The second is the family attraction. If family members do not live with the agent, he will be eager to move to them. The amount of attraction depends on the number of members that are differently located from the agent himself. Family attraction is only effective to married adults. The third aspect is registration, which is only applicable to some countries. Agent tends to live in the place where they registered. The last factor is the ethnic group from social norms, as alluded before. When the agent does not belong to the dominant ethnic group in his dwelling city, he may probably not be recognized by the major people. Thus, he seeks to migrate to other places. The cultural recognition from similar ethnic group is a weak social norm but cannot be neglected. Each decision factor is computed as

$$S_i = \mathrm{SI}_i - S\mathrm{Ave}_i - \delta_i \qquad (3)$$

where the subscript i represents the income, family, registration, or ethnic group factor. $\mathrm{SI}_{\mathrm{reg}}$ and $\mathrm{SI}_{\mathrm{eth}}$ are calculated through (1) and (2). The family satisfaction is defined as

$$\mathrm{SI}_{\mathrm{fam}} = \frac{|\mathrm{mem}_{\mathrm{loc}}|}{|\mathrm{mem}|} \qquad (4)$$

where $|\mathrm{mem}_{\mathrm{loc}}|$ is the number of members in the same city, and $|\mathrm{mem}|$ represents the total number of members.

In (3), S_i is the relative satisfaction. Positive S_i means the agent is satisfied with the current situation, while negative S_i means unsatisfied. SI_i and $S\mathrm{Ave}_i$ stand for the original individual satisfaction and the average level of one's friends. δ_i is the threshold determined by one's personality. If the agent is radical, which means low tolerance of dissatisfaction, δ_i will be a positive real number. This indicates that his S_i is easier to reach negative. When the agent is conservative, δ_i will be a negative number and the situation is vice versa.

E. Motivation, Attention and Planning

The four factors considered before may generate four independent motivations, which are the pursuits of eliminating dissatisfaction (if it has) in each aspect. The attention mechanism endows every motivation with a degree of significance, representing how eager he would like to tackle such problem. The final decision is achieved by

$$S = \alpha \cdot S_{\mathrm{income}} + \beta \cdot S_{\mathrm{fam}} + \gamma \cdot S_{\mathrm{regist}}$$
$$+ (1 - \alpha - \beta - \gamma) \cdot S_{\mathrm{ethnic}} \qquad (5)$$

where S_{income} is directly perceived, and S_{fam}, S_{regist}, and S_{ethnic} are computed as before. $\alpha, \beta, \gamma, (\alpha + \beta + \gamma) \in [0, 1)$, are

attention weights for each factor. When some of them equal to zero, it means those related motivations are fulfilled and excluded in the final decision making. S is the final satisfaction level that decides whether to migrate or not.

When an agent decides to migrate, he will make concrete steps or actions to realize his motivations. A group of such actions that fulfill a particular motivation is defined as a plan, which is generated by the planning module. For our population migration, planning is not so complicated as other applications (such as resource assignment problems in artificial intelligence). The agent only determines his destination in this process based on the future expectation.

In addition to the cognitive migration, an agent also evolves his social networks as well as potential family formation to complete procreation. In each round, an agent has a probability to get a new friend from his local "neighbors". And his current friends also have a probability to weaken their relations. This will evolve the weights of the agent's perception from each of his friends. Every qualified unmarried adult is possible to find a spouse in his residential locations to form a family. The possibility, influenced by social norms, increases with his age until 40. In other words, when an unmarried adult gets older, he will face more pressure from the society thus be more active to seek a spouse. This social norm is especially in compliance with Chinese people. Seeking a spouse is conducted in parallel with migration behavior. For fertility, every married female aged between 20 and 50 with no child will have a probability to give a new birth. The new child will be added to her family members after initialization, and the "mother" will change her procreative status into "Has Child". The total child number of one female can be set arbitrarily according to the reality. For mortality, every person has a probability to "die". Such probability also relies on his age.

Every qualified unmarried adult is possible to find a spouse in his/her residential locations to form a family. The mate selection uses the attraction score model defined as [40]

$$\mathrm{MS} = e^{-\sqrt{\mathrm{th} + \mathrm{sv}}} \qquad (6)$$

where $\mathrm{th} = 80 - \mathrm{age}_m - \mathrm{age}_f$ is the age threshold. sv means the score variables defined as

$$\mathrm{sv} = (\mathrm{age}_m - \mathrm{age}_f)^2 + (\mathrm{edu}_m - \mathrm{edu}_f)^2 + \mathrm{pre} + \mathrm{rs} \qquad (7)$$

where $\mathrm{edu} \in \{1, 2, \ldots, 9\}$ stands for educational level; $\mathrm{pre} \in \{-10, -9, \ldots, 0\}$ stands for social pressure which increases with the agent's age until 40; and rs form a uniform distribution $U[0, 9]$ is a random score. Seeking a spouse is conducted in parallel with migration behavior. The married female aged between 20 and 50 with no child will have a probability to give a new birth. The new child will be added to her family members after initialization, and the "mother" will change her procreative status into "Has Child". For mortality, every person has a probability to "die". Such probability also relies on the mortality rate by his/her age.

The whole decision cycle, as elucidated before, starts with perception and interaction, and ends with actuation. Each agent repeats such cycle constantly until he die. Therefore, the population system is evolved forward to emerge dynamical characteristics. The main loop of the evolution is presented

Algorithm 1 Agent Decision Cycle

1: Initialize *agent.attribute*, *agent.famMem*, *agent.friends*;
2: **while** *curYear* ≤ *endYear* **do**
3:   **for** each agent *a* **do**
4:     // Physical State:
5:     *a.age* ← *a.age* + 1; // age increases
6:     **if** *a.age* > 50 **then**
7:       Do die with probability *DeathRate(a.age)*;
8:     **end if**
9:     // Social Network:
10:    **if** *gender* = *F* and *age* > 20 and *age* < 50 and *IsMarried* and *!HasChild* **then**
11:      *a.FamMem* ← *a.FamMem* ∪ *GetNewAgent(a)*; // Fertility
12:    **end if**
13:    **if** *a.friends.Num* < *UpperLimit* **then**
14:      Select a candidate *cand* from the friends of each *a.friend* using Eq. (8);
15:      *a.friends* ← *a.friends* ∪ *cand*; // Add new friends
16:    **end if**
17:    **if** *a.friends.Num* > *LowerLimit* **then**
18:      Remove *SelMem(a.friends)*; // Remove friends;
19:    **end if**
20:    *IsMarried?Divorce* with *DivRate(curYear)*: Marry with a local friend with *MarRate(curYear)*;
21:    // Perceive and Interact:
22:    *a.city* ← *ResCity*;
23:    *a.income* ← *Income(a.city, curYear)*;
24:    Update the States of Each *mem* ∈ *a.FamMem*;
25:    Observe the States of Each *mem* ∈ *a.friends*;
26:    // Reasoning:
27:    Compute Relative Satisfaction S_i using Eq. (3);
28:    // Attention:
29:    Update attention weights α, β, γ;
30:    Compute S using Eq. (5);
31:    **if** S < *tollerance* **then**
32:      // Planing:
33:      $destCity_i$ ← arg max$_{a.friend.city}$ S_i;
34:      Select *targetCity* from $destCity_i$ with probability $\alpha, \beta, \gamma, (1 - \alpha - \beta - \gamma)$;
35:      // Actuation:
36:      Migrate to *targetCity*;
37:    **end if**
38: **end for**
39: *curYear* ← *curYear* + 1;
40: **end while**

TABLE I
INDIVIDUAL ATTRIBUTES

Attributes	Values	Number of Values
Gender	Male, Female	2
Age	0-5, 6-10, ..., 95-100, ¿=100	21
Res. Prov.	Beijing, Tianjin, ...	31
Res. City	Beijing, Shanghai, ...	361
Eth. Group	Han, MengGu, ...	58
Reg. Prov.	Beijing, Tianjin, ...	32
Marital Status	Married, Unmarried	2
Proc. Status	Has Child, Not Have Child	2

evolution. The objective of the former is to generate a synthetic population according to the baseline and thus determine an initial system status of the evolution. For the Chinese population scenario, we consider eight individual attributes (listed in Table I) and choose the fifth national census data (surveyed in 2000) to be the input of the population synthesis. There are two kinds of cross-classification tables in the census data. One is called short table, which contains basic personal attributes and covers the whole national population. The other is long table, which not only contains all the attributes of the short table but also includes additional features like migration pattern, educational level, economic status, marriage, and family, procreation, housing condition, etc. The statistics from the long table only cover about 9.5% of the whole target population. Another input data source is the disaggregate sample, which involves 1 180 111 individual records. Each record reveals the values of investigated attributes from a particular person (with private information omitted). In our experiments, the disaggregate sample and short table are used as the seed and marginal controls for basic population synthesis, while the long table is treated as an evaluation benchmark. The joint distribution inference method is adopted to generate the initial population [41]. Notice that in contrast with the original paper where the location only consists of 31 provinces, we have extended the synthesis into a much more fine-grained level—361 prefectures and municipalities. Initial social networks are constructed according to Erdos and Renyi random graph combined with spatial network models [42]. As some surveys indicate, random graph and spatial networks are two dominant approaches to synthesize social network [43].

The second phase is the dynamic evolution. Chinese Annual Population Statistics (2001–2015) are used to calibrate and evaluate the TiDEC model. The statistics provide annual demographic natural growth as well as death, average income, and marriage rate at the city level. We first use the early 10 years' (2001–2010) data to calibrate our model. Denote these 11 (with baseline 2000) years' data as

$$f_{[0]}(x), f_{[1]}(x), \ldots, f_{[n]}(x)$$

where $n = 10$ and

$$f_{[i]}(x) = \left(x_1^{[i]}, \ x_2^{[i]}, \ldots, x_m^{[i]} \right)^T$$

stands for the population distribution at the end of the *i*th year. $x_j^{[i]}$ means the number of population under a particular attribute

in Algorithm 1, where the "Perceive and Interact" part is computed through DNN. The initialization phase includes the agent's basic attributes, family members, and social friends, where the basic attributes and family members are created in the initial population synthesis, and the social network is generated by connecting agent pairs with probability $\lambda_{\text{agent},a}$. The probability is computed as

$$\lambda_{\text{agent},a} = e^{-\lambda \cdot \text{dist}(\text{agent},a)} \tag{8}$$

where dist is the distance between the two agents using their residential cities, and λ is a constant. We also set an upper limit of the number of friends according to the agent's age.

V. COMPUTATIONAL EXPERIMENT RESULTS

A. Experiment Design and Model Calibration

Computational experiments are composed of two sequential phases: 1) basic population synthesis and 2) dynamic
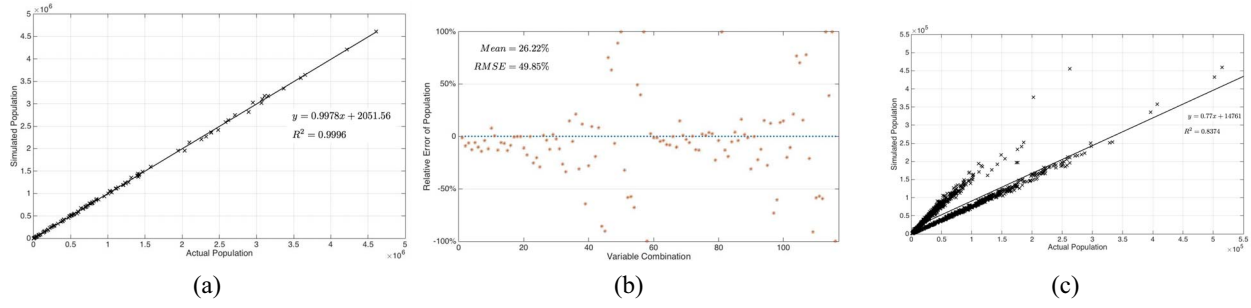
Fig. 4.   Results of basic synthetic population. (a) Gender*Res. Type*Age Inter. (b) Gender*Ethnic Group. (c) Gender*Res. City*Marital Status.

combination such as

(Gen. = Male, Age = 43, Res. City = Beijing, ...).

Actually, $f_{[i]}(x)$ can be viewed as the system state of the ith year. Thus, according to the main loop in Table I, the state transition equation from the ith to the $(i+1)$th year is

$$\left(T_{[i]} + B_{[i]}\right)^T \cdot \left(I - D_{[i]}\right) \cdot f_{[i]}(x) = f_{[i+1]}(x)$$
$$\text{s.t. } \sum_r t_{rs}^{[i]} = 1 \qquad (9)$$

where $T_{[i]} = (t_{rc}^{[i]}) \in \mathbb{R}^{m \times m}$ is the state transition probabilistic matrix. Its element $t_{rc}^{[i]}$ means the transition proportion of population from state r to state c. If r and c are only different in the Residential City, then $T_{[i]}$ is actually the migration probabilistic matrix. $B_{[i]} = (b_{rc}^{[i]}) \in \mathbb{R}^{m \times m}$ is the fertility matrix, where $b_{rc}^{[i]}$ represents the probability that an agent in state r create a new agent in state c. $D_{[i]} = \text{diag}(d_1^{[i]}, \ldots, d_m^{[i]})$ is the mortality matrix that gives the death rate of each state. In the state transition equation, $f_{[i]}(x)$ and $f_{[i+1]}(x)$ are statistical population distributions from the annual data. $B_{[i]}$ and $D_{[i]}$ are the fertility and mortality rates from the annual statistics. Thus, our objective is to compute the migration matrix $T_{[i]}$. However, such problem is an underdetermined system with m equations and $m \times m$ variables. We choose one of its solutions to be the migration matrix $T_{[i]}$.

From a microscopic view, $T_{[i]}$ is the aggregation of agent behavior, where element $t_{rc}^{[i]}$, in essence, means the agent migration probability from state r to state c. Such probability depends on the agent decision rules and ultimately by the rule parameters. Therefore, we can compute the parameters by solving

$$\hat{\theta} = \arg\min_{\theta} \left\| P_{rc}^{[i]}(\theta) - t_{rc}^{[i]} \right\|_2 \qquad (10)$$

where θ is the migration parameter vector, and $P_{rc}^{[i]}(\theta)$ is the migration probability generated by the rules.

In our scenario, the tolerance threshold δ_i is randomly set from a truncated normal distribution

$$\delta_i \in (-0.1, 0.1) \sim N(0, 0.1).$$

Therefore, the parameter vector $\theta_{rc}^{[i]} = (\alpha_{rc}^{[i]}, \beta_{rc}^{[i]}, \gamma_{rc}^{[i]})$ and

$$P_{rc}^{[i]}(\theta) = P\{S < \delta\} \cdot \left[\alpha_{rc}^{[i]} P\{\text{destCity}_{\text{inc}} = c\} \right.$$
$$+ \beta_{rc}^{[i]} P\{\text{destCity}_{\text{fam}} = c\} + \gamma_{rc}^{[i]} P\{\text{destCity}_{\text{reg}} = c\}$$

$$\left. + \left(1 - \alpha_{rc}^{[i]} - \beta_{rc}^{[i]} - \gamma_{rc}^{[i]}\right) P\{\text{destCity}_{\text{eth}} = c\}\right]. \quad (11)$$

Note that

$$E(S) = \alpha_{rc}^{[i]} E(S_{\text{inc}}) + \beta_{rc}^{[i]} E(S_{\text{fam}}) + \gamma_{rc}^{[i]} E(S_{\text{reg}})$$
$$+ \left(1 - \alpha_{rc}^{[i]} - \beta_{rc}^{[i]} - \gamma_{rc}^{[i]}\right) E(S_{\text{eth}}) \qquad (12)$$

where $E(\cdot)$ represents the expectation. By (10)–(12), we acquire can solve $\theta_{rc}^{[i]}$.

As a comparison, the proposed model is also tested in the U.S. population dataset. However, the available U.S. census data does not provide annual county statistics. Our experiment considers all the 3138 counties in U.S. homeland (excluding Alaska, Hawaii, and Puerto Rico). Two types of data, annual disaggregate samples and statistics from 2000 and 2010 census, are used as inputs. The samples contain basic individual attributes like gender, age, ethnic group, marital status, employment, etc. The migration pattern is also recorded in the data. Therefore, we use the samples to calibrate the model and evaluate the simulation results according to the 2010 overall census data.

B. Simulation Results

As the experiment design, result analysis also consists of two parts: 1) evaluation of the initial basic population and 2) annual evolutionary spatial distribution. As shown in Fig. 4, three partial joint distributions from long table are adopted as benchmarks. Fig. 4(a) focuses on Gender*Residential Type*Age Interval, where the numbers of real and simulated populations are the coordinates. Note that according to Table I, the partial joint distribution has $2 \times 3 \times 21 = 126$ combinations. Therefore, there are 126 error points in this subfigure. We can see that the regression line has a coefficient of 0.9978 with a goodness of fit of 0.9996, which means the basic synthetic population is quite accurate in this view. Fig. 4(b) presents the relative errors of Gender*Ethnic Group, which has $2 \times 58 = 116$ error points. The errors are computed by

$$\text{err} = \frac{\text{ActNum} - \text{SynNum}}{\text{ActNum}}$$

where ActNum and SynNum stand for actual number and synthetic number under each attribute combination. Clearly, all the error points are located between -100% and 100%. Only 25 out of 116 points scatter outside $\pm 50\%$. Further analysis shows that the error mostly comes from minor ethnic groups, where the small actual population number brings

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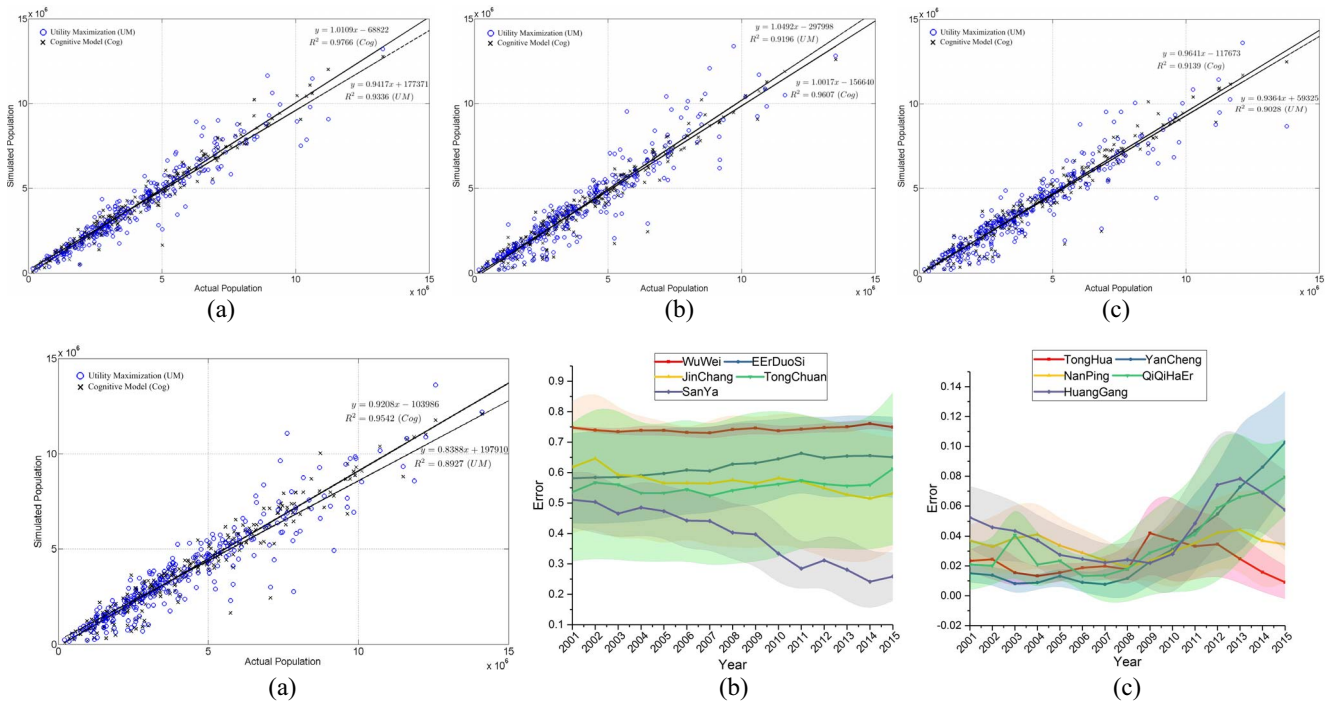

Fig. 5. Results of annual population. (a) 2001. (b) 2005. (c) 2010. (d) 2015. (e) Five cities with maximum average errors. (f) Five cities with minimum average errors.

a larger relative error. When our investigation falls down to city level, things could be worse, as Fig. 4(c) illustrates. There are $2 \times 361 \times 2 = 1444$ data points for the partial distribution Gender*Res. City*Marital Status, and they basically form two clusters. One is near 45° line, which indicates the population matches the benchmark quite well. The other lies under the 45° line, which means the population is under generated. The regression line has a slope of 0.77 and the goodness of fit is 0.8374. This is acceptable in general.

For dynamic population evolution, the simulation is conducted for 15 years, from 2001 to 2015. Limited by computational resources, the scale factor of our experiments is set to be 10 000, which means every agent in simulation represents 10000 people in reality. To test the performance of our new cognitive model, the results are compared with the traditional utility maximization. The experiments are performed for five times. Fig. 5(a)–(d) presents the spatial distribution of 2001, 2005, 2010, and 2015. The subfigures, respectively, contain 266, 286, 286, and 288 points, due to the lack of some city populations in the annual statistical report. Due to the lack of some urban populations in the annual statistical report, the comparable data contains 266, 286, 286, and 288 cities, and the subfigures, respectively, have those numbers of error points. The coordinates of each point are the numbers of real and simulated populations for a specific city. As can be seen, the simulation reconstructs spatial distributions very well in early years, but tends to under generate populations as the computation goes on. This trend is reflected by the increasing deviations of the regression coefficient. It indicates that the simulation deviates from the reality as the evolution goes on. The reason for such phenomenon may be the error propagation where former errors are passed to the following computational

cycle. In essence, it gives the following computation a more inaccurate start point. Such error accumulation, as a result, leads to larger deviations in later years. The constant item of regression line first decreases and then increases during the whole simulation. This means at the beginning, our calibrated model is able to recover the inaccuracy from the basic synthetic population to some extent. However, the total error also goes up after several rounds. On the other hand, the goodness of fit stays above 0.9 all the time. It demonstrates that random errors in each simulation round always stay at a low level. The traditional utility maximization approach is also used as an evaluation benchmark (represented by circles in the figure). The results clearly show that in each year, our cognitive method gets a slightly better performance.

For further analysis, we select five cities with maximum and minimum average errors and draw their error lines as Fig. 5(e) and (f). As can be seen, the largest relative errors stay between 50% and 75%. They also contain large standard deviations, ranging from 25% (TongChuan) to less than 5% (WuWei). In contrast, the smallest errors fall below 10%, also with small standard deviations about 5%. This result further shows that our cognitive model is able to reproduce and predict demographic spatial distribution very well.

The experiment conducted on the U.S. population dataset is shown as Fig. 6. Obviously, both regression lines have larger deviations than those in Chinese scenarios, which means both models are worse applicable for this case. However, the slope and goodness of fit of the upper line (cognitive model) are closer to 1, meaning that the synthetic data by this model match the real census data more accurately overall. Intercepts in the axis of ordinate also indicate a smaller systemic error with cognitive method than utility maximization. Therefore,

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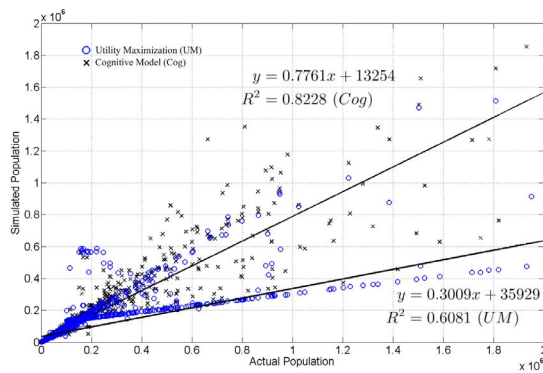
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Fig. 6.   Results of 3138 counties from U.S. Homeland in 2010.

from the perspective of statistics, the cognitive-based method can be viewed to have a better reconstruction capability. This partly manifests that the proposed model has a relatively better generalization performance.

VI. CONCLUSION

This article proposed a new hybrid cognitive architecture called TiDEC to simulate the whole process of human decision making. In contrast with the existed cognitive architectures which mainly focus on symbolic computation, it integrates DNN that can simulate the uncertainty of human perception. The proposed architecture also provides a general computational framework that can regulate the ABM development. By decomposing the model of decision making into several modules, engineers and researchers for different applications only need to consider the concrete rules in each module. This enables researchers to concentrate on domain knowledge itself and thus facilitates the ABM development in various fields. The cognitive-based method is introduced into the population evolution, which is the first time in such area. Comparative experiments on the Chinese and U.S. population datasets indicate that this method brings a more accurate modeling of decision making as well as a better generalization performance.

As a general framework, the proposed architecture can be used in various applications, not only in the simulation with artificial environments (like our population migration case) but also in the real-virtual human-in-the-loop simulation. For the latter scenario, neural network can be a suitable way and might be the only way to perceive the personal data, such as pictures, voice, motion states from blog, cell phone, and wearable devices into symbolic inputs. By such a way, a mirrored intelligent agent corresponding to the actual individual in reality can be created to simulate the individual's behavior. This is called the parallel society or symbiotic simulation. Therefore, using the actual perception data to describe, predict, and prescribe the individualȷ́s behavior is worth to be explored.

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