Complex networks and agent-based models of HIV epidemic

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Publication date
2013

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Complex Agent Networks: An Emerging approach for Modeling Complex Systems

This chapter is based on N. Zarrabi[1], S. Mei[1], M. Lees, P.M.A. Sloot, 2013,"Complex Agent Networks: An Emerging approach for Modeling Complex Systems", Journal of Systems Science and Complexity, under review.

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5.1 Introduction

Many of the worlds current problems can be described as *complex* [88, 124]. Complexity Science and Complex Systems provide new ways in which to study many natural phenomena, from protein-protein interactions [179, 50] and the spreading of infectious diseases [42, 56], to social interactions and socio-economics of modern megacities [19, 172], all the way to the human brain itself [31, 159]. A complex behavior can occur in any system that consists of large numbers of components, which interact in a non-linear way [11], such as molecular and cellular systems, organisms, ecosystems and human societies. A typical characteristic of these complex and adaptive systems is that the macroscopic emergent patterns feed back into the system and can impact the microscopic interactions. Therefore it is essential to capture the underlying mechanisms across all levels of the system. The study of complex systems provides means for understanding and predicting the behavior of such systems and therefore has the possibility of creating significant impact on understanding the complex world around us. Despite Complexity Science itself having no established theory [11, 154], the methods commonly associated with the field have been applied widely and pervasively in solving problems in biology [179], economics [132, 146], traffic [55], pandemics [56], computer science [153] and many other areas. Complex networks and agent-based modeling are perhaps the most prominent examples of such methods that provide means to study complex systems.

Complex Networks have provided insight and understanding of many complex phenomena [133, 152, 157, 162, 124, 177]. A complex network forms when the components of a system are linked and have dynamic interactions. Many real-world applications can be described as a complex network, such as social networks [116], the network of protein-protein interactions [50, 179] and the World Wide Web [6]. These networks are often huge, with some having thousands or millions of nodes. Besides their enormous size, what makes these networks complex is the dynamics of the interactions, which lead to a particular arrangement or topology of the network elements. A complex network can be described as a graph composed of a set of vertices and a set of edges. The number of edges that connect from a node to other nodes in the network is called the *degree* of the node. The frequency distribution of degrees over the whole network is an important characteristic of the network, called the *degree distribution*. The connectivity of all the nodes in the network is characterized by this degree distribution. There are various different forms of complex networks, including scale-free [15], small-world [178] and random networks [113]. A scale-free network is a form of network with a degree distribution that follows a *power law* of the form $P(k) \sim k^{-\gamma}$, where k is the degree, $P(k)$ is the probability of a node with degree k, and γ is the *exponent* of the power law. A power-law distribution implies that the majority of nodes in the network have a low-degree, but also that there are a few high-degree nodes, known as *hubs* [40, 114]. Power law distributions and scale-free networks occur in a wide range of phenomena [15, 145]. Small-world networks are networks in which most pairs of vertices are connected through a short path. The small-world effect is not confined to social networks and is also observed in many other networks such as brain networks [31] and electric power grid networks [3]. Random graphs are the simplest form of complex networks, in which every pair of nodes are connected randomly with an independent probability p. The degree distribution of such a graph is then a Poisson distribution. Random graphs however, typically do not produce the topological and structural properties of real-world systems observed in nature and society [5, 20]. Much of the research in the area of complex networks focuses on examining real-world systems and understanding what form of network structure the particular natural phenomena maps to. The scale-free structure and power-law distributions are known to occur in many real-world networks. An example is the network structure of sexual contacts of homosexual males, which is known to be scale-free with a power law exponent value ranging between 1.5 to 2.0 [104, 145]. The high-degree nodes in the sexual networks are the promiscuous individuals who may accelerate the spread of sexual transmittable infections in a population. Another example is the network of protein-protein interactions, which is also known to have a scale-free structure [83, 50]. Highly-connected nodes in such networks correspond to important proteins that play a major role in biological functions. To predict the behavior of a complex system, it is essential to start with a mathematical description of patterns observed in real-world data [172]. The definition of complex networks and knowledge of network characteristics provide such descriptions for many real-world systems. The degree distribution is an example of a mathematical formulation for the connectivity patterns in the network. Knowledge of network characteristics (i.e. degree distribution, average path length, centrality, clustering coefficient and community structure) provides insights on interconnectivity of components and global-level properties of a system [20].

Another popular method for understanding complex systems is that of agent-based modeling [23]. Agent-based models (ABMs) consist of large numbers of heterogeneous entities, known as agents, that interact with each other according to some rules; through the interaction of the agents, system level phenomena are said to emerge. In the past 20 years ABMs have been used to investigate a number of different complex systems, from traffic and parking within cities [13, 18, 55] to cellular interactions and immune system dynamics [22, 185, 101]. ABMs are especially useful for simulating the dynamics of those systems that are driven by human behavior, such as social systems [44], crowd dynamics [110, 98] financial markets [23] and economics [74]. Depending on the system under consideration the agent can be defined through a simple set of rules, or a more sophisticated entity with many interacting rules governing its behavior. In a complex social system, the definition of autonomous decision-making agents can be an abstraction of human actions in the system. ABMs are often built by first specifying the system components, compiling relevant information about entities at a lower level of the system and formulating theories about their behavior. The theories are then implemented in a computer simulation and the emergence of system-level properties can be observed [67]. Agent-based modeling provides a means to incorporate individual-level dynamics in studying complex systems.

As two of the most prominent methods of complexity science, the fields of ABM and Complex Networks have both had significant impact on many areas of science. However, each of the two methods shed light on understanding complex systems behavior from different perspectives. ABMs are built based on individual-level behaviors (also known as micro-level dynamics), while complex networks provide global-level properties (or macro-level dynamics) of the system. Therefore, to understand the multi-scale nature and complexity of many systems, such as epidemic outbreaks, information spreading on the Internet and transportation and mobility in new socio-technological systems [173], moving towards more comprehensive modeling techniques is necessary. Recent years have witnessed the emergence of a new area of work that relates to both Agent-Based Modeling and Complex Networks and formulation of multi-scale modeling [24]. Essentially, researchers have explicitly (and implicitly) started to combine techniques from both fields. That is describing physical systems using groups of agents that are mapped to complex network structures [105]. Such an approach is attractive to modelers as it provides a new and highly expressive way to describe complex systems. To the best of our knowledge [105] presented the first attempt to unify ABM and Complex Networks, since then others have looked at different ways of capturing the dynamics on networks using for instance automata [156].

This work has two important contributions to complex systems research, both related to this new area that combines complex networks and ABM. Firstly, we attempt to formally describe a form of modeling that unifies agent-based modeling and complex networks, which we term *complex agent networks* (CANs). We argue that CANs are able to capture both individual-level and global-level dynamics of a system and can naturally express the multi-scale properties prevalent in complex systems. In the CAN concept, we take advantage of both 1) structure and interaction patterns in complex networks and 2) agency and individual-level dynamics in ABM. CANs, as a new emerging paradigm for complex systems modeling, incorporate data from different spatio-temporal scales and therefore have wider implications beyond that of either ABMs or Complex Networks. The second part of the chapter brings together existing work from epidemiology, ecology and economics that have in some way utilized the CAN concept. We present a detailed example that uses CANs to study infectious disease spreading. We also present other examples of existing work that use the CANs concepts for understanding complex systems. The chapter concludes with a summary of significant research issues related to CANs. To the best of our knowledge this study is the first attempt to formalize and consolidate the research area of CANs.

5.2 Formal definition of CANs

We are surrounded by autonomous and adaptive agents, which interact and through their interactions complex collective behavior emerges. To define complex networks of interacting agents, or a complex agent network, we start with the definition of a standard complex network. A standard complex network can be defined as a graph $G = (V,E)$ where V is the set of vertices or nodes and E is the set of connecting edges. The form of network, scale-free, small-world, etc. is then determined by the arrangement of the edges E. Each vertex v will typically contain a set of state variables $s_v = s_1,\ldots,s_n$. In some particular models a set of weights w_e may be associated with edges e in E. We can then define the state of a network as $S_G = (w_e, s_v, E, V)$. Given a particular form of network there are well-established mathematical properties and tools that we can use to reason about the network and its structure [5].

We define a complex agent network in the same way as a standard complex network, where vertices are replaced by agents. The edges in the network represent the interactions, or relationships, between agents and can change over time. We define a Complex Agent Network model as Eq. 5.1 based on graph theory notation.

$$G_{\text{agents}}(t) = (\mathbb{V}_{\text{agents}}(t), \mathbb{E}_{\text{agents}}(t)) \quad (5.1)$$

$G_{\text{agents}}(t)$ is a CAN that consists of a set of time-varying vertices and edges. These vertices and edges are more complicated than those of a standard complex network. $\mathbb{V}_{\text{agents}}(t)$ is a node in CAN, which we call an *agent node*. Each edge in the set $\mathbb{E}_{\text{agents}}(t)$ connects two *agent nodes*, constrained by the formation of *interaction*. For ease of explanation, in the remainder of the text we use the term *node* to refer to a standard node in a complex network, the term *agent node* to indicate the components of complex agent networks and the term *agent* to mean an agent in the ABM or Multi-Agent System (MAS) context. Furthermore, we empower the CAN to evolve with time t. Therefore *agent nodes* can be time-varying in states and edges can be time-varying in existence and weight. A node in networks is enriched to be an *agent node*–$\mathbb{V}_i(\text{agent}_i(t), t)$ in CANs that varies with time in its internal states and behavior. An edge in networks is enriched to be $(\mathbb{V}_i(\text{agent}_i(t), t), \mathbb{V}_j(\text{agent}_j(t), t)) = \mathbb{E}_{i,j}(\text{agent}_i(t), \text{agent}_j(t), t)$ in CANs that time-varies according to the states of the two *agent nodes*. For the remainder of the text, we simplify an *agent node* to $\mathbb{V}_i^t(\text{agent}_i^t)$ and an edge to $\mathbb{E}_{i,j}^t(\text{agent}_i^t, \text{agent}_j^t)$. In what follows we define an agent node model and describe the principles we assume for agency to nodes in CANs.

5.2.1 The agent node model

We define an agent node as a system capable of flexible autonomous action in some network environment, where flexible implies a reactive, pro-active, social system [34]. Reactivity is typically a property of a standard node in a complex network, that is the node will react in some way to stimuli or input. Although nodes could also be considered as social entities, in that they interact with neighboring nodes to evolve their future state, we formulate this social ability in a much more explicit way for the agent nodes of CANs. The property of pro-activeness is where agent nodes and complex network nodes are clearly distinct. A pro-active agent node will operate with some form of goal-directed behavior and will not merely react to stimuli or input. This pro-activeness could be apparent in the evolution of an agent node's own state or in its local environment, specifically its connectivity to neighboring agent nodes. To address the pro-activeness property we define agent nodes such that they can 'sense' the stimuli of outside environment, change their own state through execution of various behaviors, interact with other agents and influence the states of the environment and other agent nodes. The definition of some basic concepts related to the internal state and behavior of agent nodes are as follows:

Definition 1 (**Status**). ***Status*** *is an abstraction of the attributes of an agent, describing the state, phase or activity that the agent is engaged in. Denote the* ***status*** *of an individual at time t by* S^t.

Definition 2 (**Event**). ***Event*** *witnesses the changes of system status at a time point t, denoted by* e^t.

Definition 3 (**Action**). ***Action*** *is the minimal execution unit to cause changes in an individual itself or the environment, and is the basic component of behavior, denoted by* Act.

Definition 4 (**Activity**). ***Activity*** *is an ordered sequence of actions that are triggered by events or initiated by individuals, denoted by* Atv. *There are internal and external activities. Internal ones only cause changes in individual status while external ones can cause changes in both the environment and individual status.*

Definition 5 (**Behavior**). ***Behavior*** *depicts individual reactions to the outside environment and is an array of observable activities.* ***Behavior*** *handles the constraints enforced by the outside environment, the internal knowledge and the current status. It's a representation of the local rules of individuals, denoted by B.*

Definition 6 (**Sequence**). ***Sequence*** *is the ordered arrangement of the elements in a certain set of actions. Consider two elements p and q. Define a logic operator '*$p \to q$*' to 'executing p persistently until executing q'; define '*$p \vee q$*' to 'currently executing either p or q'; define '*$p \wedge q$*' to 'currently executing p and q at the same time'.*

Status of an agent node

An attribute, used to describe a certain characteristic of an agent node, is called a status field. The codomain of the status field incorporates all possible values of the status field. Let the number of the status fields be M (a positive integer). The codomain of the M status fields composes an M-dimensional status space, so that the status of the agent node can be denoted by an M-dimensional vector as shown in Eq. 5.2, where $s_1^t, s_2^t, \ldots, s_M^t$ are variables of the status fields.

$$S^t = (s_1^t, s_2^t, \ldots, s_M^t) \tag{5.2}$$

Actions of an agent node

An action can be denoted by a triad as shown in Eq. 5.3.

$$\begin{aligned} Act =& \langle S_s^t, Op, S_e^t \rangle \\ & \langle S_s^t : \{s_1, s_2, \ldots, s_M\} \rangle \\ & \langle Op : f(s_1, s_2, \ldots, s_M) \rangle \\ & \langle S_e^t : \{s_1^{'}, s_2^{'}, \ldots, s_M^{'}\} \rangle \end{aligned} \tag{5.3}$$

Where S_s^t stands for the initial status, S_e^t stands for the final status and Op is the transition function or activity function.

Multiple actions that are executed in sequence can be described by a course of action (COA), $COA = \langle Acts, P \rangle$. $Acts$ is a set of actions and a subset of the complete set of actions Act^*, and P stands for the formula of the sequence order. For example, a set of actions is denoted by $COA_1 = \langle Acts_1, P_1 \rangle$ where $Acts_1 = \langle Act_1, Act_2, Act_3, Act_4 \rangle$, $P_1 = \langle (Act_1 \wedge Act_2) \rightarrow (Act_3 \vee Act_4) \rangle$.

Activities of an agent node

An activity can be denoted by a triad as shown in Eq. 5.4.

$$Atv = \langle G, Evt, COA \rangle \tag{5.4}$$

Where G stands for the goal of the activity, Evt is a set of events which can be empty, and COA is a course of action. The complete set of activities is denoted by Atv^*, $Atv \in Atv^*$. An example of an activity is given in Eq. 5.5.

$$\begin{aligned} Atv_1 &= \langle G_1, Evt_1, COA_1 \rangle \\ G_1 &= \{\text{The goal of the activity}\} \\ Evt_1 &= \{e_1 : \text{Description of event } e_1\} \\ COA_1 &= \langle Acts_1, P_1 \rangle \\ Acts_1 &= \langle Act_1, Act_2, Act_3, Act_4 \rangle \\ P_1 &= \langle (Act_1 \wedge Act_2) \rightarrow (Act_3 \vee Act_4) \rangle \end{aligned} \tag{5.5}$$

Behavior of an agent node

The behavior of an agent node is shown in Eq. 5.6.

$$B = \langle G^*, Evt^*, Act^*, Atv^* \rangle \tag{5.6}$$

Where G^* is the overall description of the goals of all activities, Evt^* is the complete set of events, Act^* is the complete set of actions and Atv^* is the complete set of activities.

The agent node

The formal definition of the agent node is shown in Eq. 5.7, incorporating status and behavior.

$$\mathbb{V}_i^t(\text{agent}_i^t) = \langle S_i^t, B_i \rangle \tag{5.7}$$

5.2.2 Networks of agent interactions

In this section, we address the functionality of complex networks in the CAN model and how to map the interactions among individuals to networks.

Functionality of complex networks in CAN

The aid of network studies is first to find statistical properties, such as path lengths and degree distributions, that characterize the structure and behavior of networked systems, and to suggest appropriate ways to measure these properties. Second, to create models of networks that can help us to understand the meaning of these properties–how they came to be as they are, and how they interact with one another. And third, to predict what the behavior of networked systems will be on the basis of measured structural properties and the local rules governing individual vertices [113]. Constructing a sexual contact network according to interaction data [113, 127] is an example that falls within the scope of the first aim. The study of network model, namely, how networks evolve to be what they currently are, is within the scope of the second aim. Studies such as spatial networks [21], planar/non-planar networks [180] and other studies investigating real-world systems e.g. train/metro networks [62, 175] fall within the scope of the third aim. The CAN study in this chapter and the detailed example infectious disease spreading (presented in the next section (Sect. 5.3) fall within the scope of the third aim. The model characterizes the complex interactions among agents though networks and support the modeling and simulation of the spreading of infectious diseases in order to help analyzing and assessing the effects of public health policies.

Mapping the interactions among agents to networks

There are various spatial models such as grids, GIS maps and networks etc., that can be used to characterize the interactions among agents, as shown in Fig. 5.1. Multiple groups of homogeneous/heterogenous agents are displayed in the shape of triangles, circles and rectangles etc. Their relationships can be mapped to grids, maps and networks. Consider those commonly used modeling methodologies wrt. description of the interactions among individuals. Cellular Automata and Partial Differential Equations usually utilize grids, ABMs and MASs usually utilize grids or GIS maps, and pure Complex Networks usually utilize networks [75, 76].

Networks can express more statistical information at the system level, e.g. through degree distributions and the shortest paths etc. Non-network spatial models can be transformed to network models (see Fig. 5.2) through the following steps.

(1) Define the exact meaning of an *interaction*. For example in some grids, an *interaction* occurs on the condition that two individuals reside in a same cell at a time point; as for GIS maps, an *interaction* occurs if the distance between two individuals is less than a predefined value (e.g. 2 meters) at a time point.

(2) Record all the *interaction* data within the system under study in a given time span.

(3) Analyze the data to get the topological structure of the *interaction* network by representing each individual as a vertex and each *interaction* as an edge.

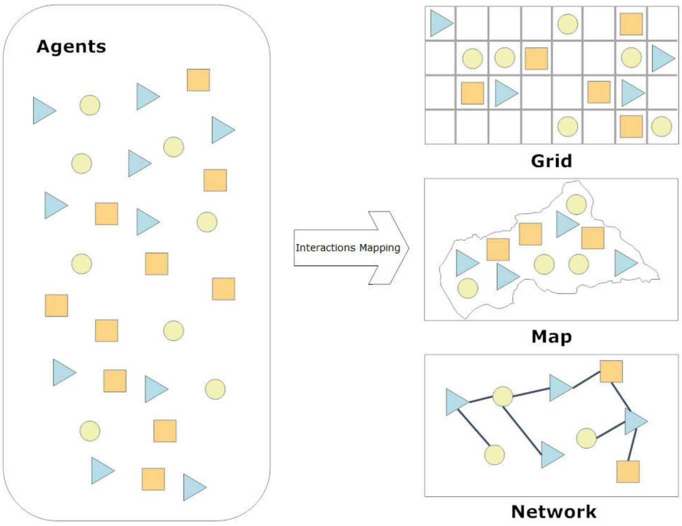


Figure 5.1: The interactions among agents and the corresponding spatial models

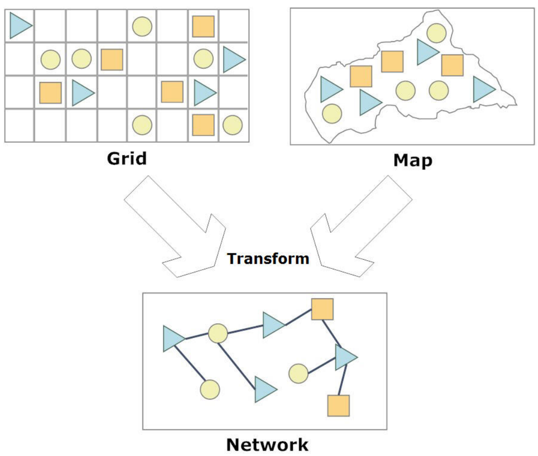


Figure 5.2: Grids and maps can be transformed to networks

5.3 Applying CANs to modeling infectious diseases

In this section we illustrate the application of the CAN concept outlined in Sect. 5.2 to a model of infectious diseases. An infectious disease results from the presence and growth of pathogenic biological agents (i.e. viruses, bacteria and microbial pathogenic agents) in an individual host organism. The spreading of infectious diseases depends on the interplay between pathogens and hosts as well as the transmission means involved. An infection can transmit through different means or contacts (e.g., air, food and blood) among people inhabiting different space. The numbers of people in various groups, such as the susceptible, the infected, the vaccinated and the recovered, are changing with time and influenced by factors e.g. self-awareness, precaution, cure and containment. An infected person conveys different infectivity due to the infection state, e.g., incubation, asymptomatic state, symptomatic state, under-treatment and recovered state. All these aspects turns the infectious disease spreading to a complex system, which displays multi-scale characteristics. To study such complex systems, one needs to consider the system dynamics at different spatio-temporal scales [186].

The spreading of infectious diseases can be investigated by modeling the population as a complex network where nodes are individuals (agents) and links are relationships [49, 142, 152, 157]. Agents provide personal heterogeneity and local disease progression at an individual level; networks continuously help to calculate the values of epidemic-related variants by collecting agents' statuses, for the sake of mimicking infectious diseases propagation at a population level. CANs provide a perfect tool for modeling such a system in which agents and networks are used simultaneously. When applying CANs to modeling infectious diseases, we need to address two issues: (1) the status and behavior of hosts at an individual level; (2) the way in which we observe and measure the system dynamics at a population level. We also define an *interaction* as a human-to-human transmission.The formation of interaction is determined by the way in which pathogens transmit between persons. For example, an interaction can be described as contagious contacts within a 2-meter distance for smallpox transmissions, or as sexual contacts or mother-to-child contacts for HIV/AIDS transmissions.

5.3.1 Modeling host agent nodes

We chose a set of societal, constitutional, medical and virological attributes such as age, gender, susceptibility, economic ranking, infection progression (whether or not being healthy, immune, infected, infectious, symptomatic, sensitive, etc.), quarantine and therapies, to compose the status of an agent node. The behavior of an agent node is $B = \langle G^*, Evt^*, Act^*, Atv^* \rangle$ (see Sect. 5.2.1). The overall description of the goals of all activities G^* is given in Eq. 5.8.

$$\begin{aligned} G^* = \{ & g_1 : \text{Living and contacting people}, \\ & g_2 : \text{Avoiding infection}, \\ & g_3 : \text{Receiving treatment after being infected and lowering self-infectivity} \} \end{aligned} \tag{5.8}$$

The set of events Evt^* that a host agent node can sense is given in Eq. 5.9.

$$\begin{aligned} Evt^* = \{ & e_1 : \text{Growing with age}, \\ & e_2 : \text{Obtaining immunity through vaccination or post-recovery}, \\ & e_3 : \text{Getting infected}, e_4 : \text{Getting quarantined}, e_5 : \text{Deteriorating of illness}, \\ & e_6 : \text{Turning early symptomatic}, e_7 : \text{Turning late symptomatic}, \\ & e_8 : \text{Turning infectious}, e_9 : \text{Starting to receive treatment (results unknown)}, \\ & e_{10} : \text{Being successfully treated}, e_{11} : \text{Being unsuccessfully treated}, \\ & e_{12} : \text{Getting recovered}, \\ & e_{13} : \text{Being added to the population (due to birth or immigration)}, \\ & e_{14} : \text{Being removed from the population (due to death or emigration)} \} \end{aligned} \tag{5.9}$$

The set of actions Act^* of a host agent node is given in Eq. 5.10.

$$\begin{aligned} Act^* = \{&Act_1 : \text{Age growing}, Act_2 : \text{Obtaining interacting neighbors}, \\ &Act_3 : \text{Getting infected by others}, Act_4 : \text{Going for treatment}, \\ &Act_5 : \text{Moving into the next infection stage}, \\ &Act_6 : \text{Healing}, Act_7 : \text{Dying}, Act_8 : \text{Vaccinating}, \\ &Act_9 : \text{Performing other precautions}\} \end{aligned} \tag{5.10}$$

The set of activities Atv^* of a host agent node is given in Eq. 5.11. Then, Atv_1, Atv_2, Atv_3 and Atv_4 are given in Eq. 5.12, Eq. 5.13, Eq. 5.14 and Eq. 5.15, respectively.

$$\begin{aligned} Atv^* = \{&Atv_1 : \text{Age changes}, Atv_2 : \text{Interaction}, \\ &Atv_3 : \text{Precaution and vaccination}, \\ &Atv_4 : \text{Infection progression and treatment}\}; \end{aligned} \tag{5.11}$$

$$\begin{aligned} Atv_1 &= \langle \{t_1\}, Evt_1, COA_1 \rangle \\ Evt_1 &= \{e_1, e_{13}, e_{14}\} \\ COA_1 &= \langle Acts_1, P_1 \rangle \\ Acts_1 &= \langle Act_1 \rangle \\ P_1 &= \langle Act_1 \rangle; \end{aligned} \tag{5.12}$$

$$\begin{aligned} Atv_2 &= \langle \{t_1, t_2\}, Evt_2, COA_2 \rangle \\ Evt_2 &= \{e_3\} \\ COA_2 &= \langle Acts_2, P_2 \rangle \\ Acts_2 &= \langle Act_2, Act_3 \rangle \\ P_2 &= \langle Act_2 \rightarrow Act_3 \rangle; \end{aligned} \tag{5.13}$$

$$\begin{aligned} Atv_3 &= \langle \{t_2\}, Evt_3, COA_3 \rangle \\ Evt_3 &= \{e_2\} \\ COA_3 &= \langle Acts_3, P_3 \rangle \\ Acts_3 &= \langle Act_8, Act_9 \rangle \\ P_3 &= \langle Act_8 \vee Act_9 \rangle; \end{aligned} \tag{5.14}$$

$$
\begin{aligned}
Atv_4 &= \langle \{t_3\}, Evt_4, COA_4 \rangle \\
Evt_4 &= \{e_4, e_5, e_6, e_7, e_8, e_9, e_{10}, e_{11}, e_{12}\} \\
COA_4 &= \langle Acts_4, P_4 \rangle \\
Acts_4 &= \langle Act_4, Act_5, Act_6, Act_7 \rangle \qquad (5.15) \\
P_4 &= \langle ((Act_6 \vee Act_7) \vee (Act_5 \rightarrow (Act_6 \vee Act_7)) \vee \\
&\quad ((Act_4 \wedge Act_5) \rightarrow (Act_6 \vee Act_7)) \vee \\
&\quad (Act_4 \rightarrow (Act_6 \vee Act_7)) \rangle.
\end{aligned}
$$

5.3.2 Measurements of the spreading of infectious diseases

A schematic illustration of infectious diseases spreading in a network is shown in Fig. 5.3. The possible status of a host can be susceptible, at incubation, at symptomatic period, recovered, vaccinated, immunized or dead. The transition of intra-host status depends on the host's infection progression and treatment reception. The edges can be changing dynamically as well to depict the removing, rewiring or reshuffling of relationships over time.

To measure the spreading of infectious diseases, we can use the following metrics.

(1) Total Cases, denoted by T, is the total of people who remain infected in a given time period.

(2) New Cases, denoted by N, is the number of people who get infected in a given time period.

(3) Deaths, denoted by D, is the number of people who die of the infection in a given time period.

(4) Prevalence, denoted by P, is the ratio of the total cases to the size of the population under study in a given time period.

(5) Incidence rate, denoted by I, is the number of new cases per population in a given time period. When the denominator is the sum of the person-time of the at risk population, it is also known as the incidence density rate or person-time incidence rate.

(6) Mortality, denoted by M, is the ratio of the deaths to the size of the population under study in a given time period.

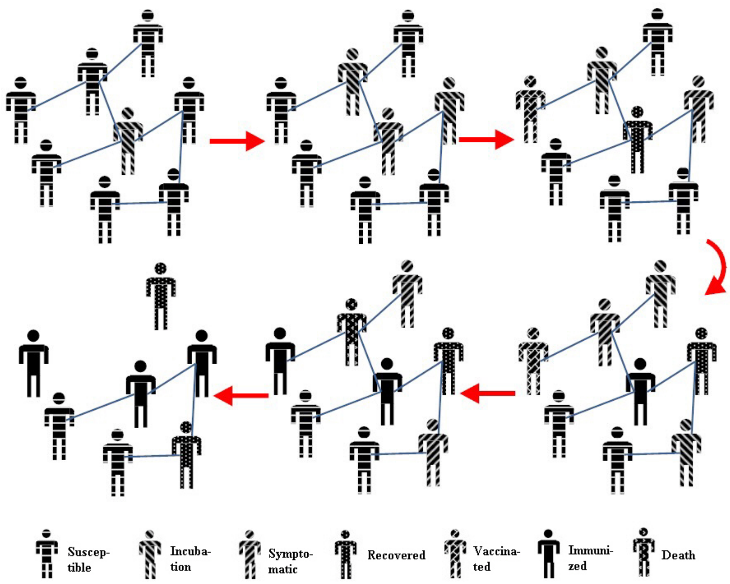


Figure 5.3: Infectious diseases spreading in a Network

(7) Reproductive Number, denoted by R, is the number of cases one case generates on average over the course of its infectious period.

Therefore, we can use Eq. 5.16 to record the status of the system (population) in terms of measuring the spreading of infectious diseases at time points.

$$\Omega = \{T(t), N(t), D(t), P(t), I(t), M(t), R(t)\} \tag{5.16}$$

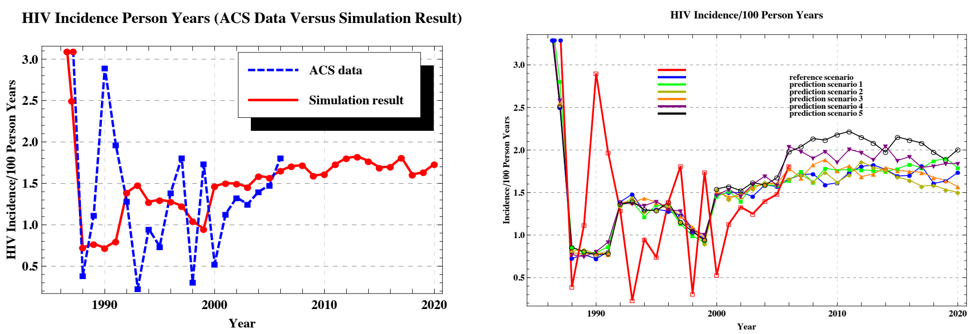
Next we need to address the calculation of Ω based on the CAN model (Eq. 5.1). According to the definition of the system, or say, the population, $G^t_{\text{agents}} = (\mathbb{V}^t_{\text{agents}}, \mathbb{E}^t_{\text{agents}})$, we can get the following sets of agent nodes.

$$\begin{aligned}
&\mathbb{I}(t) = \{\mathbb{V}_i^t(\text{agent}_i^t) \mid \text{agent}_i^t \text{ remains infected in time period t}\}, \mathbb{I}(t) \subseteq \mathbb{V}^t \\
&\mathbb{S}(t) = \{\mathbb{V}_i^t(\text{agent}_i^t) \mid \text{agent}_i^t \text{ has infected others before time point t}\}, \mathbb{S}(t) \subseteq \mathbb{V}^t \\
&\mathbb{N}(t) = \{\mathbb{V}_i^t(\text{agent}_i^t) \mid \text{agent}_i^t \text{ turns infected right in time period t}\}, \mathbb{N}(t) \subseteq \mathbb{V}^t \\
&\mathbb{D}(t) = \{\mathbb{V}_i^t(\text{agent}_i^t) \mid \text{agent}_i^t \text{ dies in time period t-1}\}, \mathbb{D}(t) \subseteq \mathbb{V}^t \\
&\mathbb{T}(t, \mathbb{V}_i) = \{\mathbb{V}_j(\text{agent}_j) \mid \exists k \in [1, t] \Rightarrow \exists \mathbb{E}_{i,j}^k \wedge \text{agent}_i^k \xrightarrow[\text{Infect}]{} \text{agent}_j^k\}, \mathbb{T}(t, \mathbb{V}_i) \subseteq \mathbb{V}^t
\end{aligned} \tag{5.17}$$

Where $\mathbb{I}(t)$ is the set of the infected individuals in time period t, $\mathbb{S}(t)$ is the set of the people who have infected others before time point t, $\mathbb{N}(t)$ is the set of people who newly turn infected in time period t, $\mathbb{D}(t)$ is the set of dead people in time period t, and $\mathbb{T}(t, \mathbb{V}_i)$ is the set of people that have been secondarily infected by the infectious individual $\mathbb{V}_i^t(\text{agent}_i)$ before time point t. Then we get

$$\begin{cases}
T(t) = |\mathbb{I}(t)| \\
N(t) = |\mathbb{N}(t)| \\
D(t) = |\mathbb{D}(t)| \\
P(t) = T(t)/|\mathbb{V}^t| \\
I(t) = N(t)/|\mathbb{V}^t| \\
M(t) = D(t)/|\mathbb{V}^t| \\
R(t) = \frac{\sum_{k=1}^{|\mathbb{S}(t)|} |\mathbb{T}(t, \mathbb{S}(t)_k)|}{|\mathbb{S}(t)|}
\end{cases} \tag{5.18}$$

The CAN model outlined above has already been used to study the transmission of infectious diseases caused by viruses such as the human immunodeficiency virus (HIV) and influenza. Modeling HIV epidemic is an example that requires a detailed description of the population network, especially for small populations in which individuals can be represented with significant detail and accuracy. Such a model also requires estimation of many parameters such as frequency of sexual actions, transmission probability per action, and parameters that shape the network structure. Shan Mei et al. [105] introduced and used the CAN concept to model the HIV epidemic among among men who have sex with men (MSM) in Amsterdam. Since the contacts among MSM play an important role in HIV epidemics, the MSM risk group in Amsterdam has been tracked for a long time and can provide realistic statistical data [1]. The experiments of the model showed a good correspondence between the historical data of the Amsterdam cohort study and the simulation results (Fig. 5.4a) [105]. The model was also used to predict the HIV spreading among the MSM population [104]. Behavior-related parameters and values, inferred from the data, are fed into the model. The authors validate the model using historical yearly incidence data. Subsequently, they studied scenarios to assess the contradictory effects of risk behavior and effective treatment, by varying corresponding values of parameters. The results show that in the long run the positive influence of effective treatment can be outweighed by an increase in risk behavior of at least 30% for MSM (Fig. 5.4b). Therefore lowering risk behavior is the prominent control mechanism of HIV incidence even in the presence of effective treatment.



(a) (b)

Figure 5.4: (a) The incidence resulting from the CAN simulation (solid) versus the ACS historical incidence data (dashed). (b) The simulated incidence for various future scenarios (1985-2020) and the ACS historical incidence (1985-2006) [104, 105].

Based on CANs, Shan Mei et al., also modeled the pandemic influenza A (H1N1) transmission through campus contacts and then forecast the effectiveness of interventions [106]. The results suggest

[1]The Amsterdam Cohort Studies on HIV infection Annual Report 2006, url: http://www.amsterdamcohortstudies.org/menu/reports/ACSannualreport2006.pdf

that pandemic influenza A (H1N1) on campus will die out even with no intervention taken; the most effective intervention is still quarantining confirmed cases as early as possible and, in addition, vaccinating susceptible people can further decrease the maximum daily number of the infected.

5.4 Other Examples of CANs

In this section, we briefly review some other applications of CANs in ecology, economics and social sciences. We attempt to accumulate experience from the extensive applications of CANs in different fields, in order to inspire further endeavors in understanding and predicting complex systems.

5.4.1 Ecological examples

Ecology is a science with a long tradition of bottom-up modeling using agent-based models [67]. Networks have been widely used to study the relations between species in natural and ecological systems [131, 113]. A first attempt to use agent-based models and networks together in order to tie the system components with global properties of the system was by Grimm et al. (2005) [68]. They introduced the concept of pattern-oriented modeling (POM) of agent-based complex systems using applications from ecology. The primary aim was to make bottom-up modeling more rigorous and comprehensive by reducing uncertainty in the model structure and parameters. A key idea of POM was "To use multiple patterns observed in real systems to guide the design of model structure"[68]. These patterns characterize the system dynamics and the variables and processes that must be included in the model so that the patterns could emerge. Using observed patterns for model design ties the system's global properties with the internal components or organization in the system. This is in line with the CAN idea, which uses ABM and complex networks to define and combine individual-level dynamics with global-level properties of the system. An example, which uses POM, is modeling the spatiotemporal dynamics of the beech forests of central Europe [135, 140, 167]. The model's structure was determined by multiple characteristic patterns. The mosaic pattern of growing stages determined horizontal spatial scale and resolution, the vertical pattern of tree sizes determined the need for height classes, and canopy gaps determined that beeches must be described individually. The former two patterns link to the global-level properties of the forests while the last one links to individual-level dynamics [67, 135].

In another study, Lurgi et al. (2010) [99] used ecological networks (relationships between species in natural systems) as inspiration to build agent-based models. They defined interactions among intelligent agents according to simple ecological rules. These rules were ecological processes that create the network of interactions in ecological systems, such as mutualism, i.e. a kind of interaction in which both species involved benefit from it. They defined interactions to produce complex networks of relationships among the entities in the system in a similar fashion in which ecological networks are formed in nature [99]. This study illustrated the validation of interactions by studying whether these interactions account for the complex network of relationships observed in the actual system. Structural patterns in ecological networks were also used to better understand system-level features like stability and persistence.

5.4.2 Economical and social examples

Complex network models are widely used to study real financial markets and industrial cluster formation that have many interacting agents with an enormous amount of information exchange [46, 84, 121, 141]. There are many interactions and communications between agents in the network, and these are subject to opinion dynamics. Jung et al. (2008) [84] investigated opinion diffusion in complex networks using agent-based models and concluded that the clustering may be regarded as groups of enthusiasts who make their own market share against the majority opinion of the market. As for industrial clusters formation, the diffusion of knowledge between organizations in the economic system is a fundamental aspect of the economic activity. Canals et al. 2005 [33] adopted the network analysis techniques and the ideas coming from recent developments of the theory of complex networks to analyze the results obtained by an agent-based model used to simulate two cases of high-tech geographical industrial clusters: Silicon Valley and Boston's Route 128 [33].

In sociology, the consensus-forming problem has been widely examined. Suo et al. (2008) [165] studied the problem of public opinion formation and concentrated on the interplay among three factors: individual attributes, environmental influences and information flow. They presented a simple model to analyze the dynamics of four types of networks and their simulations suggested that regular communities establish not only local consensus, but also global diversity in public opinions. The study shows that the dynamics of public opinion varies from community to community due to the differing degrees of impressionability of people and the social network structure of the district community. Li et al. (2010) addressed the consensus problem of multi-agent systems with a time-invariant communication topology consisting of general linear node dynamics [94]. A distributed observer-type consensus protocol based on a relative output measurement was proposed. The paper presents a new framework to address, in a unified way, the consensus of multi-agent systems and the synchronization of complex networks. The authors show that there exists an observer-type protocol which can solve the consensus problem while yielding an unbounded consensus region, if and only if each agent is both stabilizable and detectable. Other consensus-related examples include [78, 93, 117, 183, 184]. The economical and social examples are in principle applications of CANs. Importantly, applications in these fields differ from the other fields in that they address knowledge / consensus / opinion / information diffusions, instead of physical contacts between people. Examining how researchers describe the flow of these information-like virtual substances in complex networks can further refine our understanding of CANs.

5.5 Research Issues

In this chapter we have discussed a new emerging area of complex systems modeling, for which we use the term "Complex Agent Networks". To the best of our knowledge this study serves as the first collective summary of this important emerging complex systems modeling methodology. While there is clear motivation for the development of this field, at present there has been no attempt to develop these concepts. In this section we attempt to describe some of the key research questions that could, or should, be addressed to help further the development of CANs.

CANs are essentially data-driven models, they require data to help define the individual level dynamics of the agent nodes that they contain. However, ABMs in general face this same problem. Firstly, how to obtain large amounts of data that contains sufficient levels of relevant information, such that all the variations and nuances of individual behavior can be described. Secondly, how to extract valid behavioral rules from this data, such that these rules can be integrated into an ABM. One important issue for CANs in particular, is how to develop the set of known agents N_ϕ. Understanding, form data, how people adapt their local network is key to understanding the dynamics of CANs.

Additionally, CANs require data to help refine relationship patterns (network topologies). The patterns should be statistically significant to define interactions among agents and measure whether the emerged global-level properties match real-world observations. Further more, individuals' cognition of global level dynamics may inversely influence their behavior. For example, people are prone to avoid crowds (or to break ties with neighbors) with awareness of the prevalence of epidemics; organizations are more likely to move to existing industrial areas, which can provide better knowledge sharing in order to establish more connections.

Most real-world systems are complex and multi-scale. It is the individual actions that aggregate into macro-level outcomes. A prime example is the networks that are driven by human behavior such as social and sexual contacts, transportation and human mobility and networks of criminal activities. To study such systems and to predict their behavior, one needs to incorporate human behavior into agents and observe resulting phenomena across the network. CANs provide the means for such an observation through the definition of "agent nodes".

The definition of agency for nodes in a complex network would lead to a situation where nodes can automatically generate events and adapt their own connectivity. This results in a self-adaptation property of the network, which raises many interesting applications (i.e. activities occurring in social, sexual and criminal contact networks), where a node can dynamically adapt its connectivity based on the knowledge of its neighboring nodes. For example, what is the stability and resilience of an adaptive network due to random or targeted attacks, such as how criminal and terrorist networks adapt after being attacked? Or how the dynamics of individual nodes can affect the network topology [133]?

It is indeed unclear how individual-level dynamics influence the whole system and global-level dynamics influence individuals. The increasing exploration of CANs will help analyze the interplay between individual-level dynamics and global-level network properties.