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A Meta-Modeling Framework for a Specific Social Domain: Public Opinion Event

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Abstract. Due to the extensive social influence in modern information communication environment, public opinion event has caused significant attention in emergency management by the government. The formation and evolution of public opinion event is a dynamically interactive process affected by the participant's complicated psychology and behaviors. Agent-based modeling method can provide an effective and powerful tool to investigate the emerging phenomena in a social simulation system. Although many methodologies have been presented to support the standardized modeling, but the transition from expertise or theory model to computing simulation model is still a hard work for the sociologist, who usually lack of the required technological skills. In order to step over this barrier, we propose a domain-expert oriented methodology to guide the modeling process in a specific social domain, and design a meta-modeling framework based on the paradigm of Agent-Event-Environment (AEE) which can be considered as a basis of developing a visual modeling environment or tools. By the application in the real case of a major public opinion event, the proposed method has been verified effectively and efficiently. Research work of this article provides a valuable framework and methodology to deal with the transition of expertise or theoretical knowledge into computing simulation for a specific social domain.

Keywords: agent-based modeling and simulation, methodology, meta-modeling framework, public opinion.

1. Introduction

With the advent of new social media, profound changes have taken place in people's relationships and their ways of communication [1, 2]. The ongoing growth of communication technology has facilitated the access to social information which can have an important impact on public opinion in society. Some social issues, such as Twitter crisis happened in 2009 Iran Election, and "social media revolution" appeared in the Middle East and North Africa, are strongly related to information spreading and formation of public opinion [3, 4]. Recently, these social phenomena have gained great attention from many researchers of different domains [5, 6]. However, the formation and evolution of public opinion involves complex interaction process among heterogeneous population, and can result in unpredictable patterns of opinion dynamics such as polarization and fragmentation. Moreover, these highly integrated and complex social systems tend to take on greater indeterminism and unpredictability than other systems, such as physical systems. These characteristics make it impossible to adopt the traditional methods to effectively tackle the modeling problem [7, 8]. Computer simulation as a means to quantitate the complex social systems has been widely acknowledged in social sciences [9]. Agent-Based Modeling and Simulation (ABMS) may be a suitable approach for constructing and evaluating the complex systems [11, 12]. Especially, with the development of computer and information technology, it's more convenient to describe the properties and dynamics of social systems for the sociologist [13].

However, to date, the modeling and simulation of social systems is still facing some problems. A social system often contains many heterogeneous entities which interact with each other in a complicated way [9]. At the micro level, each individual itself can be considered as a complex system involving some illegible factors, such as mental attitude, belief, and emotion. At the macro level, it's very hard to capture the actual evolution process or mechanism of a social phenomenon. From the view of modelers, it's impractical to intend the simulation of a social system in all dimensions. In other words, we should focus on a specific social domain or a concrete social phenomenon which also involves the knowledge and models from different domains to be integrated in a common implementation framework. In this way, there is a great demand for a domain-expert oriented methodology to support the modeling and simulation of the social systems.

Though the achievements in scientific research have provided more opportunity and flexibility for modeling and understanding the social systems in the past years, there is still another big challenge for the domain experts (e.g., the sociologist or psychologist) that how to build and implement the simulation model based on the concept model originated from social theory. Obviously, it's a very difficult work for them who usually lack of the programming skills. The gap between design and implementation often makes the development process inefficient. As a result, they have to seek the help of computer scientists and software engineers. Similarly, the same question could also puzzle the computer scientist at the same time, and they have also been pursuing to bridge the gap over the past twenty years [9, 10, 21, 22].

To support the rapid development for the multi-agent systems, Jennings (2000) systemically proposed the theory of Agent-Oriented Soft Engineering (AOSE) to explore the role of agent-based software in solving complex, real-world problems and analyze the requirement of the development of robust and scalable software systems

[13]. Subsequently, with the development of a Model-Driven Architecture (MDA) in the soft engineering [14, 15], people have proposed the concept of agent modeling language which allows the description of complex systems at a more abstract level. It still involves the knowledge from multi-disciplinary, such as sociology, cognitive science, and artificial intelligence. In the agent modeling language, meta-models are proposed to describe the domain concepts from different views. The most representative products include Gaia [16], AUML [17], Tropos [18], AML [19], MESSAGE [20], etc. However, these languages or methodologies neither aim at any special domain, nor serve any simulation platform. Instead, the advanced programming skills are still required to achieve the design of simulation model for the domain experts. Because of the complexity of social systems, the idea that it's impractical to simulate a complex system in all dimensions has been widely acknowledged. It should be confined in a special domain, a concrete process or phenomenon.

From a user's perspective, in order to model and understand the complex system easily, the concepts in the modeling language and methodology should be similar to those used in a specific domain. The existing methodologies, including easyABMS [21] and INGENIAS [22, 23, 24], can meet the prior demands to some extent. They both aim to model social system with graphic modeling tools. The main modeling process from system analysis to simulation result analysis can be covered by them in accordance with some requirements. Besides INGENIAS provides a set of tools for modeling, code generation and simulation deployment, it allows the adoption of new notations and techniques. However, the medium programming skills are still required to make the transition from concept model to simulation model. Furthermore, the modeling ability may be weak in describing and expressing some aspects of social systems or phenomenon, such as emotion contagion, dynamic evolution of an event, and so on. So based on above analysis, we mainly focus on a concrete social phenomenon—the evolution and formation of public opinion. In order to address the application of AOSE and related techniques to model the complex social domain, we propose a four-stage methodology to construct a meta-modeling framework by defining a series of concepts close to the real system. The meta-modeling framework can be considered as a basis to develop a Domain-Specific Modeling Language (DSML) and a modeling tool for the soft engineer. The ability of the methodology in explaining the formation of public opinion and bridging the gap between domain experts and simulation implementation is tested through a case study. We anticipate that our work can help the sociologist to test the efficiency of different scenario on the resulting patterns of opinion dynamics.

The remainder of the paper is structured as follows. In the next section, we present a domain-expert oriented methodology for modeling and simulation of complex social systems, which covers the main process from system analysis to simulation implementation; in Section 3, a meta-modeling framework is proposed for public opinion event based on some system requirements; the ability of the methodology proposed in the paper is tested through a case study in Section 4; in the end, the conclusions are discussed.

2. Methodology

2.1. Model Development Process

A domain-expert oriented methodology needs to support modeling and simulation of social systems. It can guide the whole development process from system analysis to the design and implementation of simulation systems. For public opinion event, the model development process can be divided into four stages (See Fig.1): system analysis, conceptual modeling, simulation design, and code generation [21, 22].

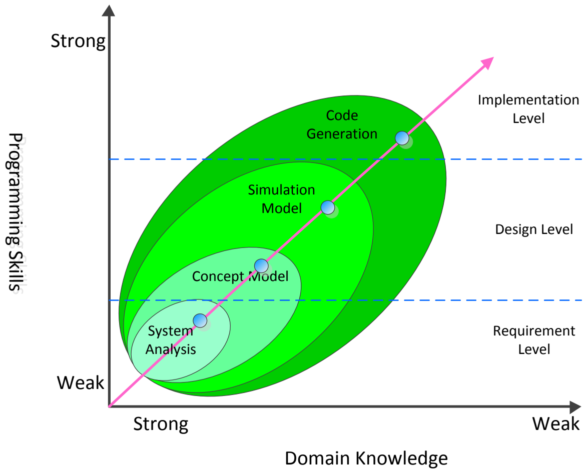

Fig. 1. The model development process

– *System Analysis*: the purposes and requirements of the model development, the understanding of the system, and the design rules and guidance are described in details;
– *Conceptual Modeling*: firstly, the main components and elements of the system are extracted and summarized, and a number of core concepts are proposed; secondly, the conceptual framework of the system is designed as a whole;
– *Simulation Design*: based on the conceptual framework, the simulation models are designed for a concrete modeling environment;
– *Code Generation*: the automatic generation from simulation models to code is implemented for a target simulation environment or platform (for example, *Repast*, *Netlogo*). The most important thing is to ensure that the code could be deployed and run on a simulation platform effectively.

The above four stages are close to the domain knowledge, computer technology and programming skills. As shown in Fig.1, the phase of System Analysis belongs to the requirement layer, which has a heavy reliance on the domain knowledge, but nothing with the programming skills; the phases of Conceptual Modeling and Simulation Design lie in the same design layer, which need both domain knowledge and programming skills; the phase of Code Generation lies in the implementation layer, which has a heavy demand on the programming skills, but nothing with the domain knowledge. However, the domain experts usually have limited programming skills. It may be very difficult work for them to design simulation models and achieve the transition from concept models to executable code. So how to make the domain experts away from the tedious work of programming and providing an effective modeling environment for simulation design is our main focus.

2.2. Transition from Concept Model to Code Generation

As said above, it's necessary to build a bridge between concept model and executable code for the domain modeling. The modeling language and visual modeling tools can help domain experts to design simulation model and achieve the rapid development of the systems of interest. Generally speaking, the basic idea is that each simulation model can be described by a unified specification and easy-to-understand notations (for example, UML), and then based on the Model-Driven Architecture (MDA) [14, 15], the transition from concept model to executable code for a target simulation environment is implemented automatically in a modeling environment. Consequently, it makes high demand on the modeling environment or tools which should have a graphic modeling capability and a suit of code generation modules. As shown in Fig.2, the simulation model is designed based on concept model in a graphic modeling environment (or tools).The modules provided by the modeling environment can be invoked to enable the code generation fast and automatically.

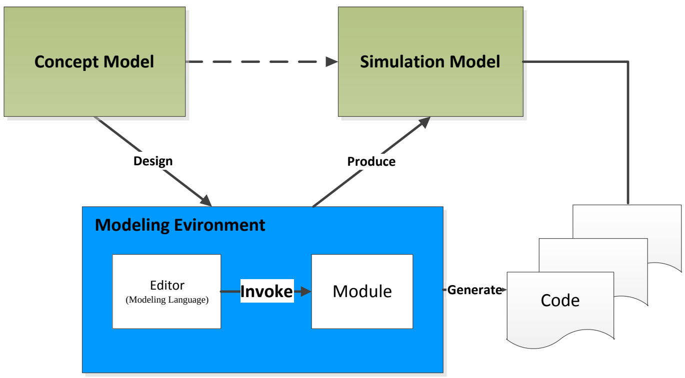

Fig. 2. The transition process from concept model to executable code

Meanwhile, simulation needs the support of model. The completeness and accuracy of the model's description would directly affect simulation results. So the concepts or elements in the modeling language need to cover all aspects of social system, or at least the key part of the system which must be considered for the research purpose. In a word, the modeling language needs to provide the design standard and general model library for the simulation design. In this way, the simulation model can be designed and described through a series of icons or notations based on some semantics, syntax, and specification in the modeling environment. Nowadays, the exiting visual modeling approach allows the sociologist to concentrate on modeling in a more abstract level.

Moreover, to run in a simulation platform, it also requires the simulation models should be translated into codes. So in order to deploy the code in a simulation platform, the abstract level should meet some requirements. For example, an object in the society could be described by a combination of some entity types in the computer world, and the entity type can be characterized by a meta-model framework. In the next section, a meta-model framework for public opinion event will be proposed.

3. A Meta-modeling Framework for Public Opinion Event

3.1. System Requirement Analysis

Constructing a comprehensive, flexible and efficient modeling framework is very important to express the objects and their relationships, and interpret the emerging of some social phenomenon. As we know, the evolution and formation of public opinion is a very complex process, which involves people's habits, their ways of communication, and social surroundings [25]. These complexities of public opinion event make the design of the modeling framework more tedious.

Firstly, the modeling framework needs to cover all the elements, phases and processes. The key elements or components should be abstracted in an appropriate level. And in order to reproduce and predict the evolution process of public opinion effectively, the dynamic mechanism of the event should be captured within a social context.

Secondly, to facilitate understanding of the complex phenomenon, the core concepts of the meta-modeling framework need to be similar or identical to those used in the specific domain.

Thirdly, as a basis of designing a visual modeling tool, the meta-modeling framework must have the combined, inheritable, extensible, and reusable characteristics. So some additional concepts and relationships need to be defined in a more abstract level.

Additionally, some auxiliary concepts need to be defined in order to maximize the ability and utility of the meta-modeling framework. These concepts can be applied to define a whole or part of each entity, which not necessarily reflect the whole entity. All the entities can be inherited from the concepts. However, because the meta-models are abstract, they can't be instantiated in the implementation phase.

3.2. Designing a Meta-modeling Framework for Public Opinion Event

As discussed above, the meta-modeling framework is a basis for developing a visual modeling environment of complex social system. Especially, from the view of the modeler, the meta-modeling framework for public opinion event needs to be designed and constructed from different perspectives (Multi-resolution, multi-level, macro-micro, and tangible-intangible). In the modeling process, we have invited domain experts (for example, sociologists, psychologist, etc.) to work together, and try to achieve the design task. We consider that three big parts, including agent, event, and environment is important to influence the formation and evolution of public opinion. So the meta-modeling framework for public opinion event can be divided into agent, event, and environment. Figure 3 shows a big picture for modeling public opinion event. It systematically describes mutual interactive relationships among population (individual, organization), event, and environment. In the following, we mainly summarize the meta-models and related concepts in details.

Agent. Agent can be considered as a map of an individual or organization in the computer world (on behalf of a person/group). It's a concrete entity which has social, cognitive, adaptive and autonomous ability within a particular social environment. An agent with a set of characteristics and rules can behave in a fashion on behalf of an individual or organization in the real world. In general, an agent can be defined as:

$$Agent_i := (\mathbf{A}_i, \mathbf{G}_i, \mathbf{RL}_i, \mathbf{B}_i, \mathbf{R}_i, f)$$

Where $\mathbf{A}_i$ represents a set of attributes of agent i, $\mathbf{G}_i$ is the goal set of agent i, $\mathbf{RL}_i$ represents social networks of agent i, $\mathbf{B}_i$ is the set of behaviors, and $\mathbf{R}_i$ represents the set of behavioral rules. And the update function f can be described as:

$$f : \mathbf{A}_i \times \mathbf{G}_i \times \mathbf{R}_i \rightarrow \mathbf{B}_i \times \mathbf{A}_i$$

It means that behaviors of the next state can be produced according to the current state, goals, and a set of rules.

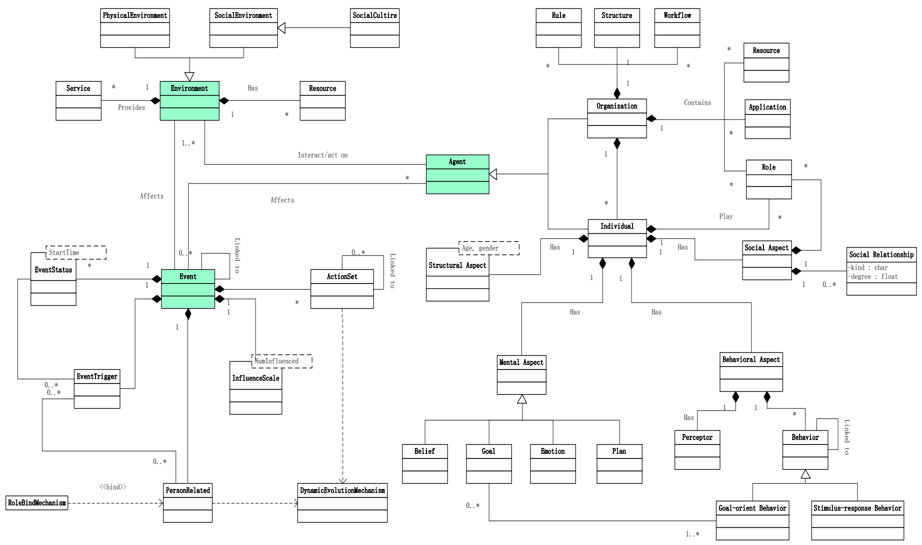

Fig. 3. The meta-modeling framework for public opinion event

Organization (*Organization*) is composed of a series of individuals with the common goal, and can also act as an entity in the computer world. It provides a framework where the individuals (*Individual*), resources (*Resource*), applications (*Application*), and roles (*Role*) coexist. An organization can be structured in some ways that would decide its structural relationships (*Structure*), social rules or norms (*Rule*), and workflows (*Workflow*). It can reflect both external and internal perspectives of modeling an organization at the same time. So the properties and behaviors of an organization contain two parts: one represents the properties and behaviors of itself, and another represents emergent properties and behaviors of all its constituents [22, 23].

Individual (*individual*) represents a person in the real world which has its own attributes and behaviors. An individual can be defined from some aspects, including structural, mental, social, and behavioral. Structural aspect (*Structural Aspect*) describes its own structure, including internal and external attributes. The internal attributes, such as age and gender, and their values specify its owner's state; the external attributes including social networks show social capability which means an individual is always linked to others with a particular environment. Mental aspect (*Mental Aspect*) means that an individual have some psychological elements, including belief (*Belief*), goal (*Goal*), emotion (*Emotion*), plan (*Plan*) and so on. Besides, it also describes some plans in order to achieve a certain state or pursue a goal. Social aspect (*Social Aspect*) represents the ability to participate in social interactions with other individuals, groups or environment. Their social relationships (*Social Relationship*), such as family, acquaintanceship, friendship, colleague, and the roles to play are also defined. Behavioral aspect (*Behavioral Aspect*) obeys "sense-think-act" mechanism, which means that the individual has the ability to sense the surrounding entities or environment (*Perceptor*), and can take on some states and react to external stimuli (*Behavior*). The behaviors include implementing its own plan, achieving a goal or task, interacting with other entities, or providing or using the service. As for behavioral modeling, there are many way to define the ability. For example, the behavior of an individual can be characterized by goal-oriented behavior (*pro-active*), stimulus-response behavior (*re-active*), or can purely be passive. In the framework, an individual can play several roles at the same time. Here the role is a very important concept, which represents either a usage of certain structural properties, execution of a behavior, participation in interactions, or possession of a certain mental state within a particular context.

Environment. Environment provides the space where the population coexist and function. It can represent physical or non-physical surroundings (such as logical, cultural, institutional, etc.) which can be heterogeneous, dynamic, open, and distributed. The physical environment (*PhysicalEnvironment*), such as building, roads, communication networks, usually has its own resources(*Resource*), and can provide some services (*Service*); the non-physical environment (*SocialEnvironment*) can be constituted by social culture (*SocialCulture*) and the development level of a society. In most cases, the environment can be abstracted as a series of application program interfaces to achieve the interactions with other entities.

Event. The event can be defined as a set of attributes and behavioral rules which have some effects on social process or phenomenon. The event always happens within a particular social context or environment, which can be considered as a special environment. It mainly describes the related objects, process, and state of a real event. Generally speaking, it contains some certain parts, including status (*EventStatus*), the trigger conditions (*EventTrigger*), the related population (*PersonRelated*), incidence (*InfluenceScale*) and a set of behaviors (*ActionSet*). We also design several mechanisms to explain the dynamic process of the evolution of public opinion. The personnel binding mechanism and dynamic evolution mechanism can reflect the instantaneous state, dynamic change and timeliness of an event. Every time the trigger happens, the personnel binding mechanism need to be called immediately.

4. Case Study

It's widely acknowledged that the spread of information (rumor, gossip) could shape the public opinion in a society [26, 27]. In the case study, we mainly focus on the negative information (rumor) spread and negative opinion contagion in the context of the 2009 Urumqi unrest.

4.1. Context and Investigation

In order to better facilitate modeling and simulation of the 2009 Urumqi unrest, it's necessary to briefly review the process of the event. In June 26, 2009, the "Shaoguan incident" happened and two Uighur youth dead. Then the World Uyghur Congress (WUC) and other organizations or persons attempted to incite ethnic antagonism, and fabricated rumors to spread quickly via Word of Mouth, the Internet, mobile phone, online social networks, and other social media. The antagonism widely evolved among the Uighur masses unaware of the truth until the event broke out in July 5, 2009. As said above, we can see that the evolution of the event is extremely complex, where multiple factors are intertwined at the same time. For the sake of simplicity, we will set the study scope in the Urumqi City, and consider the Uighur masses (about 280.74 thousand), a terrorist organization (WUC), and some other factors about the environment and event as the modeling objects.

For the evolution and formation of public opinion, the mechanism in one country may be different from other countries due to the social difference and diversity among them. As said above, it's crucial to make the mechanism clear in order to model the system effectively. However, how to validate the simulation framework and its result is also a problem [4]. All the phases of a simulation (from initialization to analysis of the results) need the real data's support. Luckily, in 2011, National University of Defense Technology (NUDT) and other academic institutions designed a questionnaire on the public opinion in Changsha city, China [30]. Through the exploratory factor analysis on the survey data, a set of attributes or factors and the corresponding quantitative methods were identified. In the survey, the factors which affect the spread behaviors could be divided into two parts. One is the subjective internal factors including physiological, psychological and acquired factors (such as age, gender, education, occupation, etc.), and another external factors including the property of the opinion, the strength of an event, and so on. The survey is conducted in Changsha city, and the differences may exist for Urumqi city. Considering the similar culture between them, we assume that the survey data can be suitable to Urumqi city, which also constitutes the basis for developing and designing the simulation system.

4.2. Model Design

Agent Model. The Uighur masses (Data resource: 2010 census data), WUC, and the government can be modeled as agent models. Because INGENOUS has provided a flexible and extensible mechanism to adapt new notations and techniques, we use the visual modeling tools, named INGENIAS Development Kit (IDK), to design the simulation models in the following. For example, each Uighur citizen in the Urumqi city can be described as a concrete agent model in the computer world following a unified framework. We have taken advantage of synthetic population method [29] to generate artificial population for the Uighur masses in the Urumqi city based on the 2010 census data and survey data. In the synthetic population, each individual has certain attributes, including demographic, socioeconomic, and cultural or psychological characteristics (for details, see Table 1).

Table 1. Parameters for an individual

Attribute		Description
socioeconomic	a_i	Age of individual i, $a_i \in [0,100]$
	g_i	Gender of individual i, $g_i \in \{male, female\}$
	H_i	Family individual i belongs to (unique ID of household)
	R_i^H	Family role of individual i, $R_i^H \in \{Grandfather, Grandermother, father, mother, \ldots\}$
	R_i^s	Social role of individual i, $R_i^s \in \{infant, student, worker, unemployed, retiree\}$
	$\mathbf{P}_i^H$	Home address of individual i, $\mathbf{P}_i^H = \{longitude, latitude\}$
	SN_i	Social networks of individual i which list up all the other individuals with different relationship types
psychological	I_i	Influence which means the capacity to have an effect on the character, development, or behavior of someone or something, or the effect itself, $I_i \in [0,1]$
	C_i	Conformity which represents the behavior in accordance with socially accepted conventions or standards, $C_i \in [0,1]$
	T_i	Trust which represents the acceptance of the truth of a statement without evidence or investigation, $T_i \in [0,1]$
	S_i	Stubborn which means it's hard to change one's opinion or attitude, $S_i \in [0,1]$
	o_i	A view of an individual formed about something, $o_i \in [-1,1]$

We first design Uighur citizen in IDK. As shown in Fig.4, each Uighur citizen has its own mental state, and can play different roles in the evolution process of the event, such as a rumor spreader or receiver. The mental state can be regarded as an semi-entity which represents some facts or a combination of one or more variables. The values of these parameters can be assigned based on the survey data [30]. (The semantics of the notations can be found in Ref. 23).

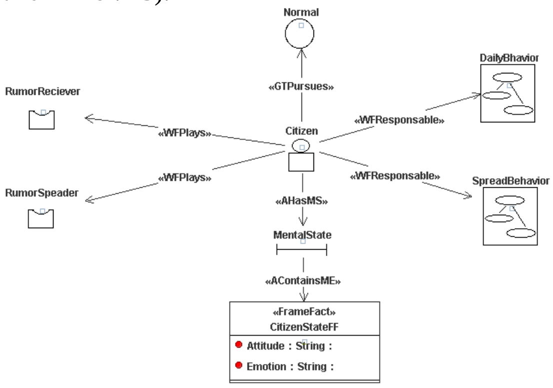

Fig. 4. The Uighur citizen model

The behavior of each Uighur citizen can be divided into two parts: daily behavior and interaction behavior. In fact, the spread behavior can be a special kind of the interaction behavior. As shown in Fig. 5, the interaction between two citizens may achieve a common goal, and follow certain specifications (For example, UML specification). Figure 6 shows the modeling diagrams of the information (rumor) spread behavior. From an individual perspective, spreading and receiving a piece of information can be considered as a cyclic behavior. Firstly, the receiver perceives the content of a piece of information, including property, intensity, concern degree, and so on. In turn, the information itself can also influence the receiver's status and behaviors (such as changes in attitude or emotion). And the information source could be another citizen, which means that interaction between them happens when receiving or sending a piece of information. When the information is received by the receiver, a decision is made to judge whether to spread. If it is, the social relationship networks of the receiver will be accessed to search the objects immediately; if not, the spread behavior ends, and the receiver quits the simulation. When a certain condition is met, the spread behavior will end at a time.

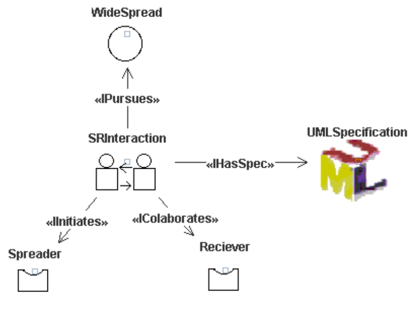

Fig. 5. The interaction behavior

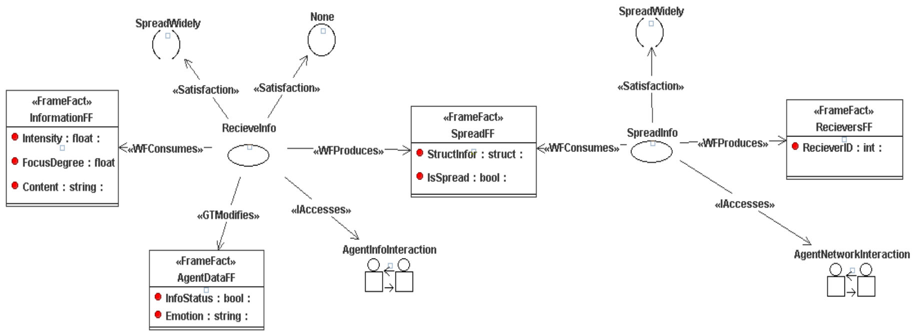

Fig. 6. The spread behavior

For the purpose of modeling the formation and evolution of public opinion, the opinion interaction model should be discussed in detail. We assume that receiving information is a premise to opinion evolution for an individual, and the way to spread information is through interpersonal communication. The mechanism of selecting spread objects depends on social networks [27, 28]. As discussed above, the interaction behaviors can be divided into two parts. Firstly, an individual will interact with a piece of information, and the interaction process can be formalized as follows:

$$\begin{cases} o_i(t+\tau) = o_i(t) + [o_h - o_i(t)] \times A_h \times [1 - I_i(t)], & Max\{I_i, S_i, C_i, T_i\} = I_i \\ o_i(t+\tau) = o_i(t) + [o_h - o_i(t)] \times A_h \times C_i(t), & Max\{I_i, S_i, C_i, T_i\} = C_i \\ o_i(t+\tau) = o_i(t) + [o_h - o_i(t)] \times A_h \times T_i(t), & Max\{I_i, S_i, C_i, T_i\} = T_i \\ o_i(t+\tau) = o_i(t) + [o_h - o_i(t)] \times A_h \times [1 - S_i(t)], & Max\{I_i, S_i, C_i, T_i\} = S_i \end{cases} \tag{1}$$

Where o_h represents the property of a piece of information ($o_h \in [-1,1]$), A_h is the authority of the information ($A_h \in [0,1]$), and τ is the time step for interacting with a piece of information.

Secondly, the interaction between a pair of individuals i and j can result in the change of their opinions. Suppose individuals i and j can influence each other, the opinion interaction rule can be defined as follows:

$$o_i(t+T) = o_i(t) + [o_j(t) - o_i(t)] \times f_{ij}, \quad if \left| o_j(t) - o_i(t) \right| < \varepsilon \tag{2}$$

Where $f_{ij} = [1 - \left| o_i(t) - o_j(t) \right|] \times I_j(t) - I_i(t) \times [S_i(t) - C_i(t)]$, which means the influence level, T is the time step and ε the confidence of an individual. Here we make an assumption that from an individual view, the interaction between an individual and a piece of information happens prior to the interaction with other individuals, so the constraint $T \geq \tau$ can be concluded.

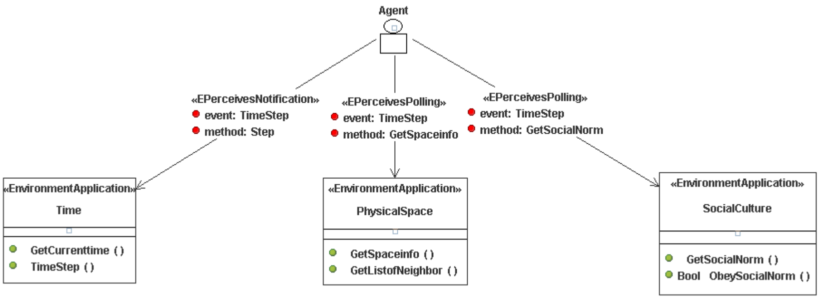

Fig. 7. The environment model

Environment Model. The environment model mainly describes the spatio-temporal relationships between the population and physical environment, and the constrained relationships between the population and social norms or habits. As shown in Fig. 7, it reflects that an agent always situates in a particular geographical environment, and is influenced by the social environment (such as customs, laws, or moral constraints).

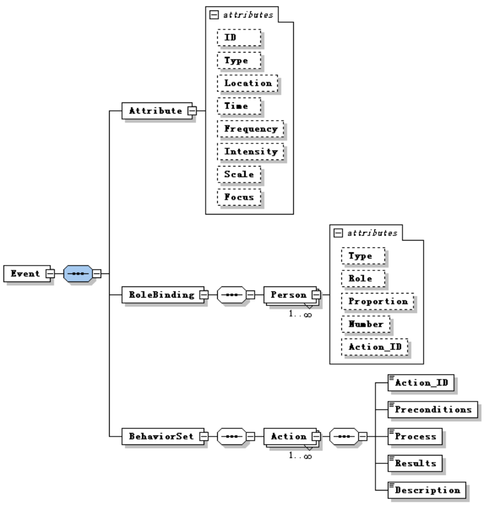

Fig. 8. The template of describing a typical event

Event Model. As previously mentioned, the event model is descriptive. We adapt the method of normative template method to design the event component. As shown in Fig.8, the event model is composed of basic properties, personnel, and a set of behaviors. The basic properties include the type, time, intensity, scale, and so on. The personnel means those involved in the event, including their roles and behaviors. And each action has its own premises, processes, results, and description. These template data can be stored in XML files.

However, there is no component available to describe the event model in IDK. So we make an extended development to introduce a module which can support for modeling an event and generating code deployed in our simulation platform-OneModel [31, 32].

Here, we re-utilize some notations in IDK such as *GeneralEvent* and *Role* to describe the event model, as shown in Fig. 9, which can accord with the formal description of a typical event.

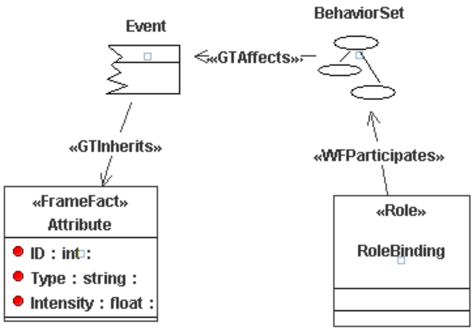

Fig. 9. The event model

4.3. Data Preparation

The simulation implementation needs the support of data. As said above, we adapt synthetic population method to generate 280.74 thousand Uighur citizens in Urumqi city based on the 2010 census data and the survey data. Each piece of data represents a concrete agent in synthetic population. Additionally, with the advice of the social psychologist, the values of psychological attributes can be assigned to every individual based on a certain generation algorithm [29]. Meanwhile, it can make sure that the generated population is heterogeneous. The general statistics of the synthetic population are given in Table 2 and 3 respectively.

Table 2. Basic Uighur population statistics for Urumqi city

General		**Social role distribution**	
Total Population	280,740	Students	67,658
Men	141,773	Workers	150,756
Women	138,967	Retiree	43,524
Average household size	3.26	Unemployed	18,809

Table 3. Values of psychological attributes for different type of population

Type	**Influence**	**Conformity**	**Trust**	**Stubborn**
Opinion Leader	[0.8, 1]	(0.2, 0.5]	[0, 0.2]	(0.5, 0.8)
Ignorant	[0, 0.2]	[0.8, 1]	(0.2, 0.5]	[0, 0.2]
Bounded Confidence	(0.2, 0.5]	(0.5, 0.8)	[0.8, 1]	(0.2, 0.5]
Self-opinionated	(0.5, 0.8)	[0, 0.2]	(0.5, 0.8)	[0.8, 1]

4.4. Simulation Set-up

The IDK provides the modules or plug-ins to generate the code automatically. After the simulation models are designed with the IDK editor, the code generator module can be invoked to transform the model diagrams and the data (Deployment file) to code for a particular simulation platform. As shown in Fig.10, we deploy the code in the parallel simulation platform-OneModel [31, 32] developed by our research team.

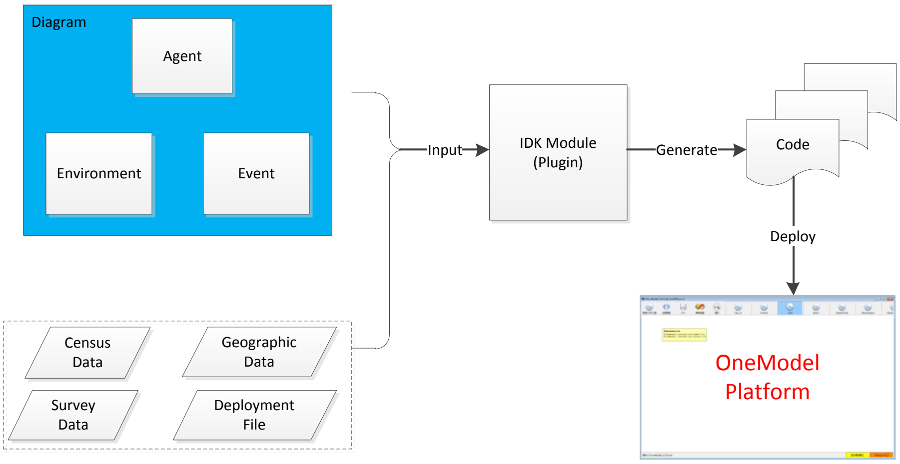

Fig. 10. The deployment process of simulation

Table 4. Parameters for simulation run

Parameter	Brief description	Value
Initial number of spreader (proportion of population)	The information or rumor resources, which can be selected randomly or determinately.	$3.5e^{-5}$
Simulation period (day)	The whole time of the simulation run	10
Simulation time step (day)	The time resolution of the model. At each time step, the state of each agent is updated.	0.5
Spread probability	The probability of spread upon an interaction with a spreader.	0.3
Property of information, o_h	Represents the attribute, quality, or characteristic of something.	-0.8
Authority of information, A_h	Represents the power to influence others.	0.6
Bounded confidence threshold, ε	Determines a process of opinion dynamics that may lead to a consensus among the agents.	0.2

To investigate the effectiveness of our modeling framework, we mainly have studied on the former process before the Urumqi unrest broke out. The simulation period is 10 days, that is, from June 25 to July 5, 2009.The simulation step is 12 hours, and it means one tick represents half a day. The initial values of parameters used in the simulations are given in Table 4.

4.5. Results Analysis

To reduce the error effectively, the simulation in the same initial conditions should be implemented repeatedly many times because of its stochastic characteristic. We carried out 50 batches of implements, and the average results are obtained under the assumption that the government didn't take any control strategy. Here we select several indicators to analyze the results, namely the scale of the rumor spread and the distribution of the opinion. Figure 11 shows the spread scale of the rumor, where X axis represents the time (in days), and Y axis the proportion of the population who know the rumor. As shown in Fig. 11, the proportion increases sharply in the first three days, while relatively stable in the next two days. It may be due to the fact that the heat of the rumor is relatively high, and over time, it will cool down gradually. On the 6th day, there is suddenly a large increase which lasts for about two days. This probably reflects the release of Rebiya Kadeer has some incitement effect on the opinion evolution. Thereafter, although there is a little growth, the proportion becomes stable, maintained at the 0.64.

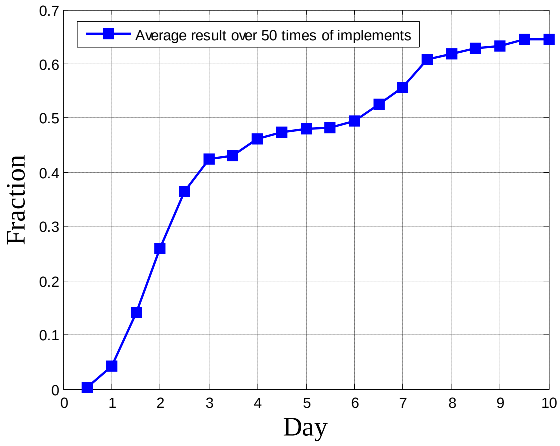

Fig. 11. The fraction of the Uighur citizens who know the rumor in Urumqi city

Figure 12 shows the dynamic changes of three kinds of opinion over time, where the red represents the negative opinion which can have a negative effect on the social harmony and stability, such as panic, anger, and so on. As can be seen, the negative opinion rises to the dominant trend. This explains that from the beginning, the proportion of negative opinion rose slowly and smoothly, and with widely spread of the rumor and the accumulation of negative opinion, a large and rapid rise happens. It also reflects that the rumor may have a desired effect on the Uighur citizens, which means that it's necessary that the government must take some control measures to some extent.

We also investigate the distribution of negative opinion (<-0.6) in the population of different ages. Figure 13 shows the dynamic process when the simulation runs at the tenth day. It can be seen that the proportion of negative opinion in the people between the ages of 20 and 30 is bigger than others, which illustrates the negative opinion spreads more easily in the younger people. The result is in line with the fact that the younger people may have played an important role in some terror events.

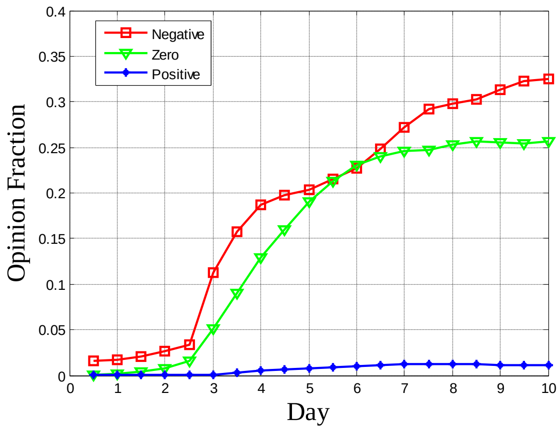

Fig. 12. The fraction of the three kinds of opinion over time

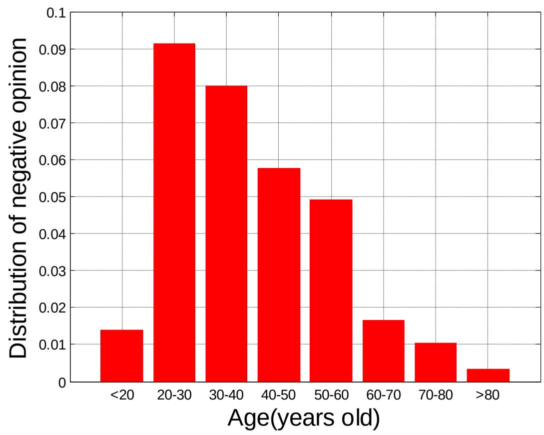

Fig. 13. The distribution of negative opinion in the population across different ages

The methodology of ABMS makes it possible to obtain rich information both at macro and micro levels. The simulation can't only show the dynamic evolution of the system, but also a concrete partial phenomenon. Figure 14 shows the evolution of negative opinion in the fourteen street offices of Tianshan District over ten days (z-axis represents the ratio of the number of population with negative opinion to the total population number in a street office). It can be seen that the negative opinion spreads more quickly in Jiefang South Street, Jiefang North Street, and Yan'an Street, where the similar evolution process can be found as a result of their similar population structure and social culture. However, the negative opinion in Yanjian Street and Yanerwo Street can't spread widely and the proportion is relatively small. It illustrates that the evolution and formation of public opinion has the characteristic of regional differences.

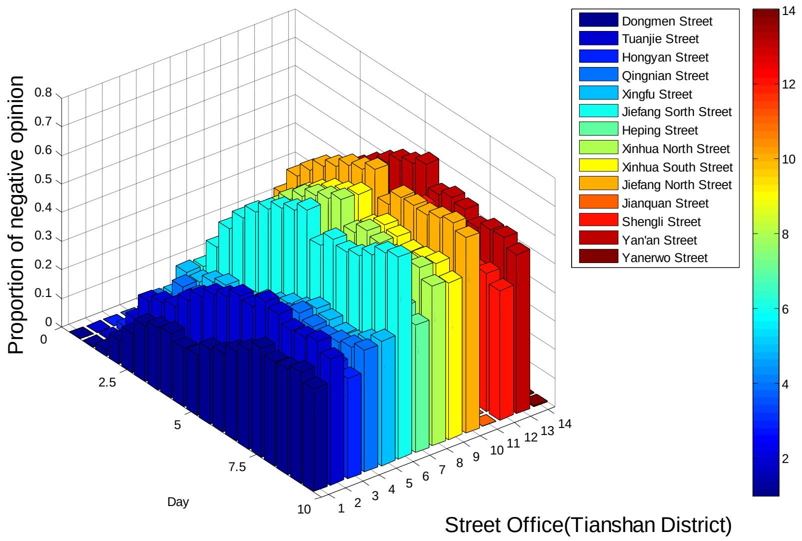

Fig. 14. The evolution of negative opinion in Tianshan District, Urumqi City

However, nowadays, there is no survey data on psychological or behavioral responses to receive a rumor or a piece of information within a particular social context. The simulation results can just show no more than a macro trend, which can provide some references for the emergency management.

5. Case Study

Agent-based modeling and simulation has become an effective way to study the complex social systems. The complexity of the systems requires the integration of knowledge in different fields and the participation of multi-discipline experts. For a long time, the computing problem of the complex social systems hasn't only attracted the attention of the sociologist, but also the researchers from different fields and disciplinary, including physics, psychology, computer science, and so on. Consequently, a series of fruitful research have been achieved. Unfortunately, due to the domain limits, these studies haven't been well integrated systematically due to domain limits. One of the biggest obstacles to carry out the quantitative research on complex social systems can be summarized as follows: the expertise or theory models mastered by the sociologist can't be translated into computing simulation models due to lack of the programming skills. As a start to resolve the contradiction, a domain-expert oriented methodology is proposed in the paper. With the purpose of developing a suit of visual modeling tools for the sociologist (domain experts), a meta-modeling framework based on the concept of Agent-Event-Environment (AEE) for public opinion event is designed according to some system requirements, and the effectiveness of the methodology is validated through a case study.

However, there is a long way for us to develop the visual modeling tools. The current simulation models are designed with the IDK where we have just made some reasonable extensions. Our final goal is developing a suit of domain-specific, easy-to-use, user-friendly, and graphic modeling environment or tools to support the standardization of modeling as certain special social domains. At present, the simulation is implemented in our own platform-OneModel. Its performance need to be tested and compared with other platforms (for example, Repast and Mason). In a word, modeling and simulation of the complex social systems will require the deep collaboration with the domain experts to expand and strengthen the scope and capacity of the modeling method or language. Through continuous feedback and iterative collaboration, the validity and robustness of the methodology can be deeply tested in the future.

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