# Agent-based Social Network Model of Construction through Analysis of Japanese General Social Survey Data

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***Abstract*-This research attempts to construct an intimacy-based social network model by the analysis of all types of personal relationship networks in the real world based on the Japanese General Social Survey, and apply the network model in simulations of social phenomena. We conducted an agent-based simulation to build this social network based on a virtual city model, achieved by geographic information and census systems. Immunization awareness diffusion in the constructed social network is shown in this paper as an example of the social phenomena simulation. In addition, we aim to expand the application of this social network model in future social simulation research.**

***Keywords- Social Network Model; Agent-Based Simulation; Japanese General Social Survey; Social Phenomena Simulation***

## I. INTRODUCTION

Personal networks are representations of the relationships between an individual and others, through which individual interacts with friends, family, acquaintances, work colleagues, etc. Large populations and their personal networks comprise a population-wide social network. Such a social network consists of individuals or organizations, and indicates the ways in which they are connected through various social familiarities ranging from casual acquaintances to close familial bonds.

Social network analysis was introduced by Moreno in 1934 [1]. Original research about social networks aimed to explore the ways in which group relations serve as both limitations and opportunities for a person’s actions and therefore for their personal psychological development based on statistical methods. In 1969, J. A. Barnes [2] reported that the study of social networks was based on basic notions of graph theory, as is the identification and analysis of social cliques. Moreover, with the development of computational sociology, Lynne Hamill and Nigel Gilbert [3] designed a social circle model, which fit well with the sociological observations of real social networks. Social network research has become a prominent research field in sociology, anthropology, social psychology and other branches of science. The importance of social networks for understanding and predicting human interaction and behaviour is generally acknowledged [4].

In literature, traditional social network generation models have focused on reproducing the global characteristics of social networks, such as path length, clustering coefficient and degree distribution without the intention to explicitly model the choice behaviour of actors [5]. There were six representative topological social network generation algorithms concerning traditional social network generation models: Ring Lattice, Small World, Erdös Random, Core Periphery, Scale Free and Cellular [6]. Since the mid-twentieth century, many social network models created by random linking have been based on these algorithms. However, all people in these models choose their partners according to the same algorithm without considering their personality and social characters. Some types of people (infants, unemployed persons, etc.) may not necessarily have many social links in reality. Unlike previous models, our research attempts to generate a social network by considering the features in terms of personal relationship networks at the individual level by statistical analysis of data from the Japanese General Social Survey (JGSS), which provides us with a basis of reality about existing personal networks. In our model, all individuals in the population and their personal networks are connected to an overall social network.

However, one of the most famous previous statistical approaches to modeling social networks was the Exponential Random Graph Models (ERGMs) [7], in which the presence and absence of network ties were accounted for, and which provided a model for a network structure. In the case of ERGMs, the focus was not on modeling the choice behavior of humans but rather on the more direct modeling of the social structures this choice behavior might produce. More recently, researches about the geographical distribution of personal networks by the survey method were introduced for the purpose of revealing geographic and mobility aspects of social networks and social interactions [8, 9, 10]. Considering the difficulty of collecting data at a social level due to the high project cost and technical limitations of survey strategy, most studies in this field use a small-scale survey. Personal networks and respondents in these studies are selected indiscriminately. Conversely the data we used in this



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research are from a sophisticatedly sociological survey belonging to the global General Social Survey group, which is the longest running project from 1972. The strict survey data create a more realistic social network model in this research.

Moreover, although research about social network generation with topological graph theory has made decisive progress and is commonly found in literature, research into social networks from an agent-based simulation perspective is relatively new. Most previous research has focused on agent-based social network models to simulate specific situations, such as recommendation systems [13, 14], travel behavior of individuals and traffic systems [15], rather than the generation of social networks. The premier research in the agent-based network field, developed by the Los Alamos National Laboratory in 2004 [11, 12], studied the algorithmic and structural properties of a very large, realistic social contact network and applied the results to a social network for the city of Portland, Oregon, USA. Although this research considered the heterogeneity of humans and combined realistic estimates of population mobility, the social network that was generated was a social-contact network, which does consider the levels of intimacy between humans in the network. Other expressive associated research [3, 16], which is relatively new, created large social networks in agent-based models by incorporating different sizes of personal networks, high clustering and other key aspects of large social networks, though the initial number of human agents in the social network varied due to randomness. Differing from previous agent-based social network research, we attempt to construct a much more realistic spatial model by utilizing real geographic information about a specific city area and considering geographical closeness as a contribution to intimacy between the human agents in the model.

In this paper, we focus on the universality and intimacy existing within personal networks, which are embedded in a population-wide network structure in reality, as well as the structure and influence of a social network on individual behaviours. Ordinarily, personal networks hold particular characteristics deriving from distinct persons so that the aggregation of the personal networks is always complicated. Over the past decades, experimentation, controlled observation and questionnaires were the primary means by which to collect valuable insights into the mechanisms of personal network structure. As one of the typical questionnaires, the General Social Survey is an open sociology data source, which was proposed to add network survey items from 1984 [17]. In this research, we propose the construction of an agent-based social network model by analyzing all types of personal relationship networks in the real world from the Japanese General Social Survey.

The structure of the paper is organized as follows: the details of data analysis will be shown in Section Ⅱ. The social network model, which includes not only the geographic composition of society but also a population-wide network composed of personal relationship networks of all individuals in the society, will be introduced in Section Ⅲ. As an application of our social network, we attempt to simulate immunization awareness diffusion phenomena and vaccination behaviour in the personal networks in Section Ⅳ. In the final section of this paper, conclusions and implications are proposed.

## II. SOCIAL NETWORK ANALYSIS OF JGSS DATA

This research attempts to analyse the Japanese General Social Survey in 2003<JGSS-2003>, which is completed by more than 7000 men and women of ages 20-89 living in Japan from late October to mid-November 2003, and conducted by the Institute of Regional Studies at Osaka University of Commerce and the Institute of Social Science at the University of Tokyo. JGSS-2003 uses both interviews and a self-administered questionnaire method for each respondent. The interview questionnaire records fundamental personal information about each respondent. The self-administered questionnaire B consists of core questions about the personal network of respondents. Two types of questions are listed in the questionnaire B: questions about the name generator [18] and questions about the position generator [19]. Name generator elicits the names of persons and characteristics of the persons with whom the respondent discussed personal matters during the last six months. In contrast, the position generator uses the samples of structural positions salient to a society (occupations, authorities, work, units, class, or sector). Furthermore, relationships between ego and contact for each position can be identified. Name generator focuses on the intimacy between humans, while position generator certifies the diversity of personal contacts within the network of acquaintances.

In the name generator portion of the questionnaire, respondents are asked to list three primary connections: “people with whom you discuss matters important to you or those in whom you confide”; “people with whom you discuss Japanese politics, elections or politicians. You may include people with whom you occasionally talk about the above topics”; and “people with whom you consult about your job or whom you ask for advice concerning your job”. Every respondent names up to a maximum of four actual persons for each criterion. Respondents should write down full names, initials or nicknames in their answer sheet so that interviewers can identify them afterwards. Respondents can write the same names as responses to different questions. Respondents are also asked to identify the relationships between the persons whose names are mentioned in their answer sheet. Because position generation proposes to investigate the diversity of personal contacts, in the position generator portion, respondents are asked several additional questions about information of the persons they have mentioned such as: age, sex, job, relationship, background, etc. Such personal information is directly related to the personal network diversity of respondents so that we can determine the type of acquaintances the respondents are more intimately involved with.

There are 1706 valid respondents in self-administered questionnaire B. Primarily, we collect fundamental information about these 1706 respondents from interview data using JGSS-2003. Depending on the personal information collected, we can then classify all respondents into 270 types. Additionally, we analyse the personal social networks of the respondents



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according to their answers in self-administered questionnaire B, and then calculate their leadership degree within their personal social networks. Furthermore, we compare the individual type and characteristics in the personal social network of each respondent. Depending on such comparisons, we aim to find the mechanism of relevance between the individual type and their personal social network. Finally, after introducing our data analysis result into a city model and substituting characteristics of personal social network for every person in the city model, we are able to generate an entire social network model.

### *A. Classification of Respondents*

First, we divide all respondents into several types. Considering that JGSS chooses respondents according to special standards so that all answers have universal meaning, we are able to ensure that all individual types existing in the real world are included in the survey data and that every type of individual is able to represent a general group of people in society.

We extract five types of necessary information (sex, age, marital status, job and household type) from the interview data, and then use the information to define the human type as shown in Table 1.

TABLE 1 DEFINITION OF HUMAN TYPE: HUMAN (SEXX, AGEE, MARRYY, JOBB, HOUSEHOLDD)

| **Index** | **Definition** |
|---|---|
| Sex (sexx) | Male: sexx=1<br>Female: sexx=2 |
| Age (agee) | Twenties : agee=2, Thirties : agee=3,<br>Forties : agee=4, Fifties : agee=5,<br>Sixties : agee=6, Beyond seventies: agee=7;<br>(★There is no data about people younger than 20 years old) |
| Married status (marryy) | Married : marryy=1<br>Unmarried: marryy=2 |
| Job (Jobb) | worker: jobb=1, retired: jobb=2, student: jobb=3,<br>house worker (housewife): jobb=4, others: job=5 |
| Household type (householdd) | One-person household: household=1<br>Two-person household: household=2<br>Three-person household: household=3<br>Four-person household: household=4<br>Five-person household: household=5<br>Six or more than six-person household: household=6 |

Originally, depending on these five indices defined in Table 1, all respondents can be classified as one of 720 (2*6*2*5*6) types. However, some types cannot objectively exist in reality (such as students over 60 years of age). Therefore, we strike the impossible types from the list of 720 types, leaving 270 types for analysis.

### *B. Personal Social Network Intimacy*

Considering that the answers of respondents can be repeated in different questions according to the questionnaire structure, we assume that if the same name is written many times under different questions, then the respondent has a deep relationship with the name holder. To evaluate the degree of intimacy between respondents and acquaintances whose names appear on the answer sheet, we count the number of the occurrences of each name. We define the number of the occurrences of a name as equal to the intimacy degree between the respondent and the name holder (Depending on the answer sheet, each name may occur a maximum of three times.). Additionally, we can also calculate the intimacy degree between the acquaintances themselves in the same manner. By combining the intimacy between the respondent and his acquaintances and the intimacy between the acquaintances themselves, we can generate a personal network of the respondent.

According to JGSS, we constructed 1706 personal networks for each valid respondent. Fig. 1 depicts and example personal relationship network of a respondent in JGSS-2003. The person in the centre of the network graph represents the respondent; his answer sheet is shown on the left. ‘B’ and ‘E’ are the same person whose name is ‘NAME2’, so the intimacy degree between respondent and ‘B’ (or ‘E’) is equal to 2. Additionally, ‘NAME2’ knows ‘NAME3’ and ‘NAME4’, who are also included in the respondent’s personal social network. Moreover, according to the position generator portion of the survey in in questionnaire B, we determined that ‘NAME2’ is the wife of the respondent in reality. Similarly, we are able to identify the relationship between the respondent and everyone existing in his personal network and calculate the intimacy degree between any two people within this network.



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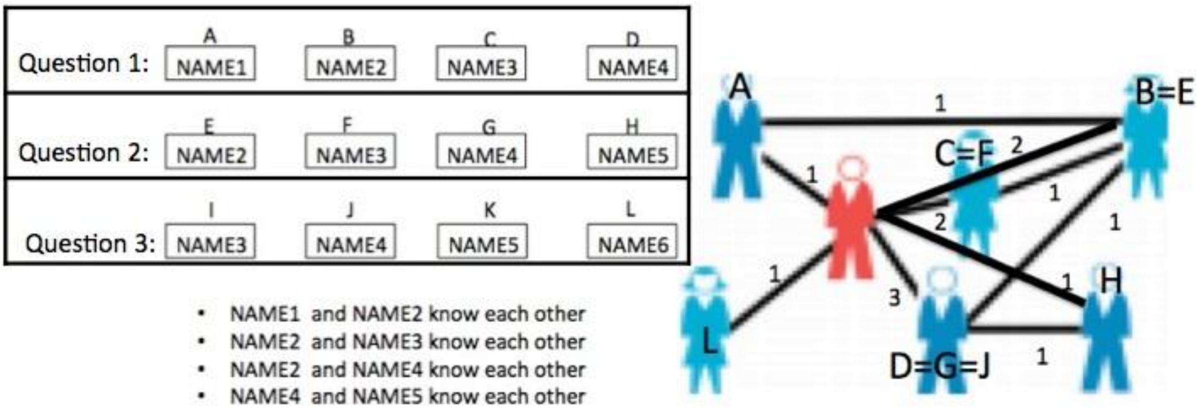


Fig. 1 A personal relationship network of one respondent in JGSS-2003

*A. Leadership Degree in Personal Social Network*

Based on the personal social network of each respondent, we can also calculate the leadership degree of each respondent in his own personal social network by the graph entropy method [7]. We define the leadership degree of the respondent 'i' as $Ld_i$, and calculate the graph entropy as follows:

$$\text{Graph Entropy } E_{all}: \quad E_{all} = \sum_{i,j} p_{i,j} \log\left(\frac{1}{p_{i,j}}\right) \; ; \qquad p_{i,j} = \frac{w_{i,j}}{\sum_{i,j} w_{i,j}}$$

Where $w_{i.j}$ is the weight between 'i' and his relevant people 'j', and $p_{i,j}$ is the ratio in the entire network. The edge entropy of respondent 'i' is defined as $E_i$:

$$E_i = \sum_j p_{i,j} \log\left(\frac{1}{p_{i,j}}\right) + \sum_j p_{j,i} \log\left(\frac{1}{p_{j,i}}\right)$$

Where $\overline{E_i}$ is the graph entropy, when the graph delete respondent i.

$$\text{Leadership degree of i:} \quad Ld_i = \frac{\overline{E_i}}{\log\left(\dfrac{E_{all}}{E_i}\right)}$$

We use the graph entropy method to calculate the leadership degree of all respondents in JGSS, with the statistic results shown in Fig. 2.

| Leadership degree | |
|---|---|
| N($L_i$>0) | 1274 |
| $L_i$=0 | 432 |
| Average | 3.03 |
| Median | 3.07 |
| Standard Deviation | 0.69 |
| Minimum | 1.55 |
| Maximum | 4.98 |

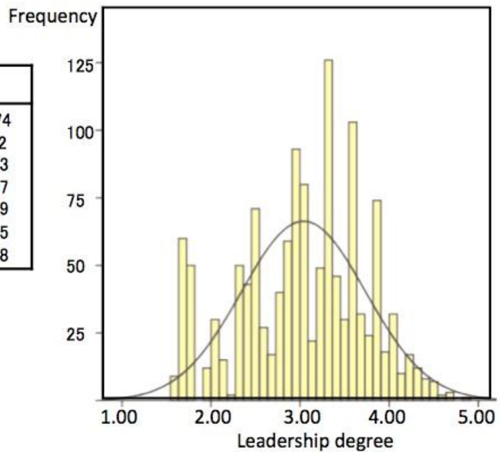


Fig. 2 Leadership degree statistics

Moreover, we compare the leadership degree result with each index of respondents and find that relations between leadership degree and sex, marital status, and household type are not signifiant. Conversely, the leadership degree of respondents is related to their job status. A statistical chart comparing respondents' job status and their leadership degree is shown in Fig. 3. The mean value or variability of leadership degree among workers is marked higher than the other respondents with different job status. Particularly, nearly all respondents with a leadership degree beyond 4.00 are workers. Additionally, considering that few of students are chosen as respondents, the sample size of students is smaller than that of other job types.



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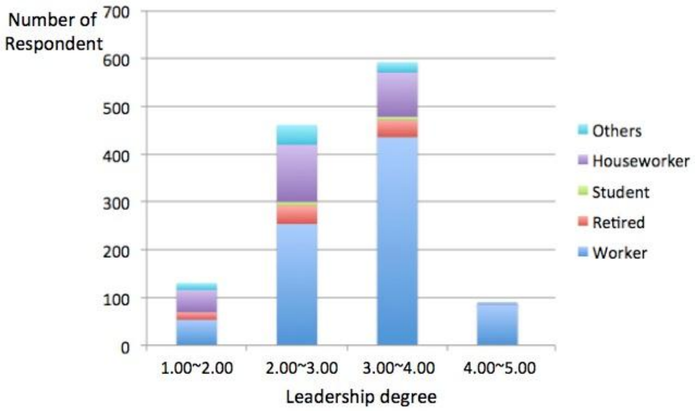


Fig. 3 Job status of the respondents and their leadership degree

## B. *Characteristics of Personal Network for Each Type of Human*

To establish the connections between the fundamental properties of respondents and their corresponding personal network, we collect statistics about each type of person and their corresponding personal relationship network. According to the survey, there are ten types of relationship between humans. Type1~Type3 refers to relationships between family members: Type1 refers to a spouse (husband or wife); Type2 refers to a parent or child; and Type3 refers to a brother, sister, other family member or relative. Type4~Type6 are human relations with relevance in the workplace: Type4 refers to a superior or subordinate at tge workplace; Type5 refers to a coworker (except superiors or subordinates); Type6 refers to another business associate. Type7~Type10 stands for other types of relationships such as neighbor, friend, etc. Here we will show an intimacy characteristic of one type of human: 'Human(1,5,1,1,4)' represents a group of men, 50~60 years old, married, workers, and members of households including four people. Table 2 summarizes all ratios of relationships in the personal networks of Human(1,5,1,1,4) for each type of relations. According to the statistics, workmates (Type4~6) occupy 43.860% of relationship networks for 'Human(1,5,1,1,4)' on average, which suggests that workmates are the main personal contacts for workers over 50 years of age. In addition, although type 'Human(1,5,1,1,4)' has a much greater number of relevant people in the workplace rather than in the home, only 6.667% workmates have a very good relationship (intimacy degree=3) with 'Human(1,5,1,1,4)'. Conversely, 31.25% people from type 'Human(1,5,1,1,4)' claim that their wives are the persons they are closest to.

TABLE 2 RATIO OF INTIMACY DEGREE FOR EVERY RELATIONSHIP TYPE IN PERSONAL SOCIAL NETWORK OF 'HUMAN(1,5,1,1,4)'

| **Relationship Type** | **Intimacy Degree** | | | **Ratio of Each Type** |
|---|---|---|---|---|
| | **1** | **2** | **3** | |
| Type1 | 34.375% | 34.375% | 31.25% | 18.713% |
| Type2 | 71.429% | 23.810% | 4.762% | 12.281% |
| Type3 | 69.230% | 30.769% | 0.000% | 7.602% |
| Type4, Type5, Type6 | 73.333% | 20.000% | 6.667% | 43.860% |
| Type7~Type10 | 63.333% | 33.333% | 3.333% | 17.544% |

In addtion, we can also generate statistical features about the leadership degree of 'Human(1,5,1,1,4)', as shown in Fig. 4. Depending on the statistics, the average leadership degree of 'Human(1,5,1,1,4)' is greater than the total average leadership degree. Therefore, we can presume that the leadership degree of 50-years-old workers is always higher than the average standard in reality. Similarly, we can also analyse characteristics of the personal social network for all 270 types of respondents.

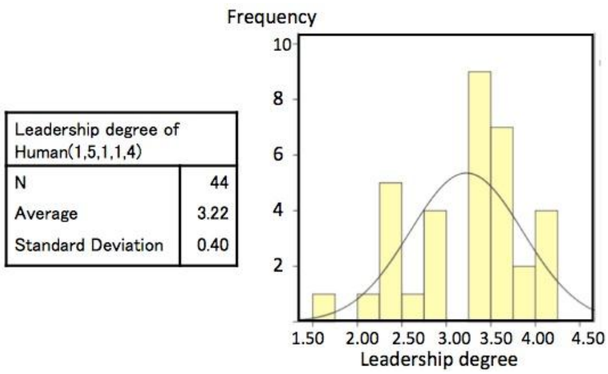


Fig. 4 Statistics about leadership degree of 'Human(1,5,1,1,4)'

As has been noted in this research, we attempt to analyse features in terms of personal social networks at the individual level from the Japanese General Social Survey for the purpose of generating an agent-based social network model. In the next section, we introduce the application of the data analysis result and the method of social network model construction.



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## III. AGENT-BASED SOCIAL NETWORK MODEL OF CONSTRUCTION

In this research, we conduct an agent-based simulation to generate a realistic spatial social network based on a virtual city model by obtaining real geographic information of a specific city area and considering geographical proximity as a contribution to intimacy between humans.

This model is developed with the agent-based simulation language SOARS[1] [20, 21] (Spot Oriented Agent Role Simulator), which is a Java-based simulation tool.

### A. *Geography-Based Virtual City Model*

In previous work [22], Ichikawa constructed a virtual city model, in which people were related by social structure estimation from the Geographic Information System (GIS) and Japan Census from E-STAT[2]. The content of the virtual city model [22] is shown in Fig. 5. There were two elements in the virtual city model: human agents and spots. Human agents represented people living in the city; spots included homes, schools, workplaces, etc. In the virtual city model, all human agents were built with a series of individual properties such as age, sex, household structure, social role, etc. Behaviours of human agents depended on a bundle of rules that apply to agents. For example, a six-year-old child agent had a family consisting of a father, mother, and a one-year-old brother. On weekdays, he went to primary school at 8:00am, which was near his home. At school, he communicated with other students. At 3:00pm, he returned home. According to previous work, we are able to presume the population-by-age composition and the household composition of the city based on the city survey, geographic information and census data.

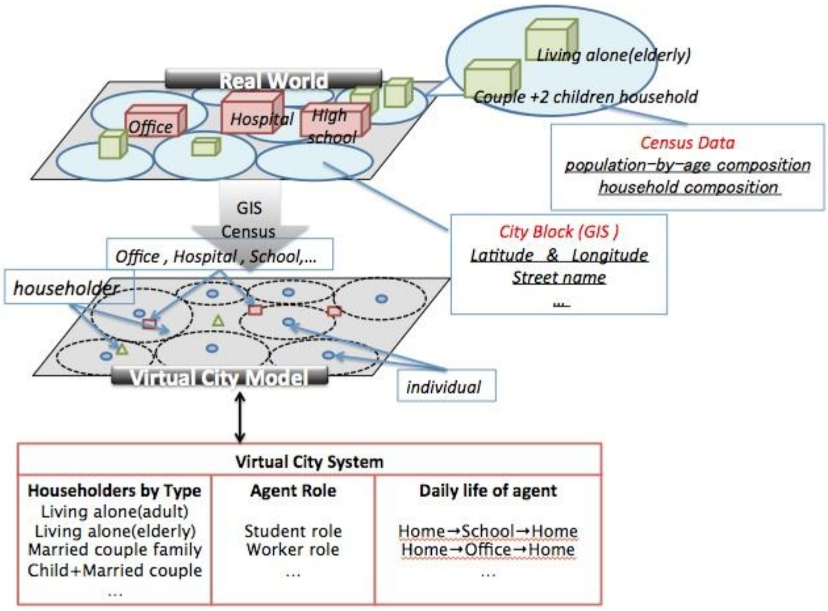


Fig. 5 Virtual city model

Specifically, we are able to construct a virtual city model for a specific area: Izu-oshima Island [23, 24], which is a city under the administration of Tokyo. The information known about virtual Izu-oshima model is shown in Table 3. Because it is possible to generate the information about household composition, population-by-age composition, location of institutions and additional information by access to the community survey about any city in Japan from the Japanese Census, we can generate any geography-based virtual city in Japan.

Though the previous virtual city model considered the geographic social structure so that the constructed model was similar to the real world and used an agent-based simulation to reflect the domestic and social activities of human beings, it was not enough information to represent the real social network because it did not take into account the intimacy between human agents. Considering that each agent in a virtual system composes the entire social network, each referent has some essential connection. All agents should be affected by the relevant people in their personal social network. In the real world, such networks only depend not on geography, but also on each agent themself. Therefore, we aim to generate a spatial social network based on the previous geographically-based virtual city model. Intimacy in the social network is estimated by the JGSS data analysis results.

[1]SOARS Project. http://www.soars.jp.
[2]Statistics Bureau. http://www.e-stat.go.jp/.



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TABLE 3 DETAILS OF GEOGRAPHICALLY-BASED IZU-OSHIMA CITY MODEL

<table>
<tr><th>City Composition</th><th colspan="2">Parameter</th><th>Value</th></tr>
<tr><td rowspan="3">Human Agent<br>(Number: 7584)</td><td colspan="2">Age, Gender, Household, Job, Marital status.</td><td>Fixed from Census from E-STAT</td></tr>
<tr><td colspan="2">Location of workplace/school, location of home</td><td>Population location is deduced from Census mapping with GIS from E-STAT</td></tr>
<tr><td colspan="2">Parameters associated with Daily Action</td><td>Refer to Comprehensive Survey of Living Conditions.<br>(Ex: Home (8:00)→Primary school(16:00)→Home→…)</td></tr>
<tr><td rowspan="12">Spot (Place)<br>in the virtual city</td><td>Household (home)<br>(Number: 4098)</td><td>9 types<br>(Single (over 65 years old); Couple+1 child; Couple +2 children…)</td><td rowspan="12">Latitude and longitude of the spot is fixed from GIS<br>Location of spots decides the home, school, workplace location of human agents<br>Scale and structure of spots is from city survey</td></tr>
<tr><td rowspan="6">Factory/office/<br>enterprise (Number: 1620)</td><td>Staff number: 1~4<br>(Number:1182)</td></tr>
<tr><td>Staff number: 5~9<br>(Number: 228)</td></tr>
<tr><td>Staff number: 10~19<br>(Number: 136)</td></tr>
<tr><td>Staff number: 20~29<br>(Number: 30)</td></tr>
<tr><td>Staff number: 30~<br>(Number: 40)</td></tr>
<tr><td>Another<br>(Number: 4)</td></tr>
<tr><td>Kindergarten<br>(Number: 5)</td><td rowspan="4">Students number in each school can be drawn from city survey</td></tr>
<tr><td>Primary school<br>(Number: 3)</td></tr>
<tr><td>Middle school<br>(Number: 3)</td></tr>
<tr><td>High school<br>(Number: 2)</td></tr>
<tr><td colspan="2">Retirement home（Number:20）<br>Long stay (3) Others: (17)</td></tr>
</table>

*B. Application of JGSS Data Analysis*

We propose to introduce our data analysis results into a virtual city model and construct an entire social network based on the geographically based virtual city. In this social network, all leadership degrees and relationship intimacy degrees of each person are based on the JGSS data analysis results as described in Section Ⅱ.

To achieve our purpose, we first constructed a geographically based virtual city. Family information (including family numbers, their social role, and family roles) and information about workplaces (human agents who work in the same workplace) were included in the original geographically based virtual city. Next, we input the value ('1', '2', '3') of relationship intimacy degree to each person in a personal network. The selection of value is based on the ratio of the relationship in this type of person's personal relationship network for each relationship type. Similarly, we chose a human agent from type Human(1,5,1,1,4) as an example. The setting of intimacy degree with other persons in Human(1,5,1,1,4)'s personal network is shown in Fig. 6.

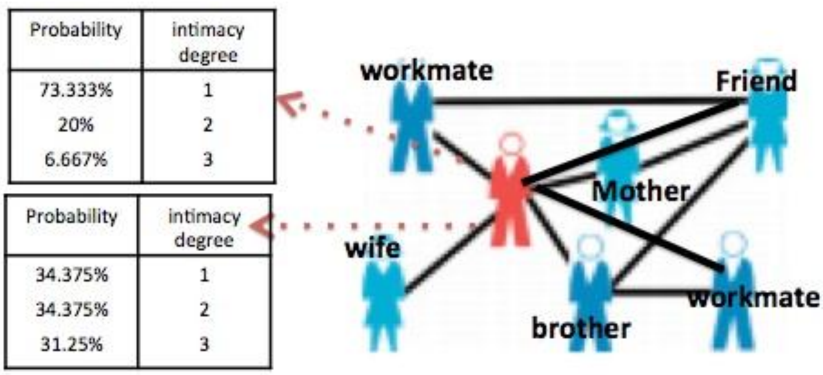


Fig. 6 Model to determine intimacy degree for a 'Human(1,5,1,1,4)'



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*C. Social Network Model*

By applying data analysis results to the virtual city model, we were able to generate an entire agent-based population-wide social network. In this research, we constructed a social network model of Izu-oshima Island. The process of social network generation can be organized as follows: first, we classify all agents into 270 types according to their age, sex, marital status, job and household role. Second, by applying the JGSS analysis results into the virtual city model, we calculate the relationship intimacy degree for each type of human agent in the model. Finally, by building all personal networks for all human agents, we generate the population-wide social network of Izu-oshima Island. Because there is no social network data available regarding people younger than 20 years old in JGSS, the intimacy degree of all agents under 20 years old was set to a random number between 1 and 3.

According to this process, we constructed 7584 personal networks for all human agents in the model, each embedded in a population-wide network structure of the Izu-oshima city. Fig. 7 illustrates the visualization of the constructed social network. Each node on the graph represents one of the human agents, which are named as ‘VC_Human1’, ‘VC_Human2’…‘VC_Human7584’ in the model. The edges in the graph are double arrows, which illustrate the personal contact of each agent in the social network model. We generated this social network figure with the Yifan Hu multilevel layout algorithm [25] by Gephi[3] network graph visualization software [26].

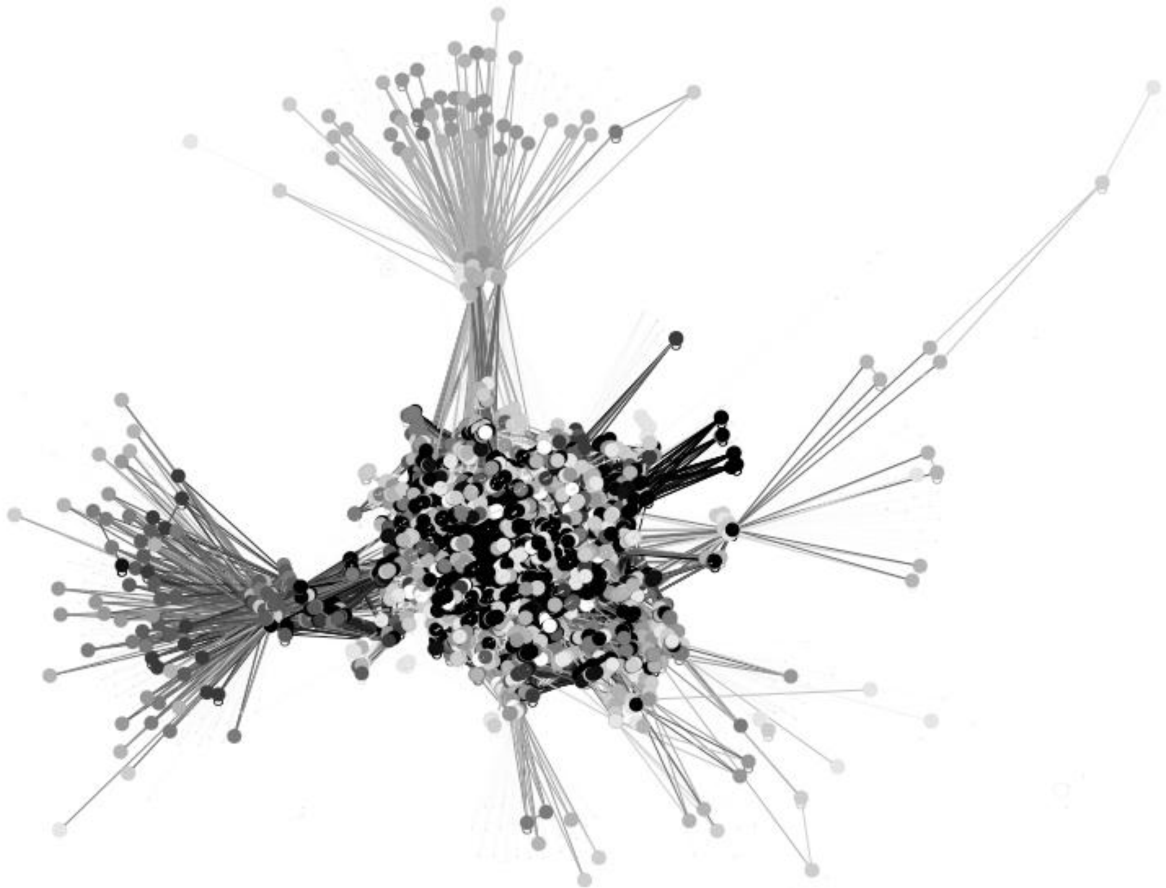

Fig. 7 Visualization of social network of Izu-Oshima

Fig. 8 illustrates an example of personal work, which is one part of the entire social network, also achieved with Gephi[3] software. I As shown in Fig. 8, ‘VC_Human317’ and ‘VC_Human7405’, ‘VC_Human5786’, ‘VC_Human418’, ‘VC_Human6509’ and ‘‘VC_Human5092’ work in the same office; the relationships between them are ‘officemate’. All personal networks of these six workers are shown in Fig. 8. In addition, the relationship between each pair of the human agents is recorded at the edges. For example: ‘VC_Human316’ and ‘VC_Human318’ are children of ‘VC_Human317’ (In Fig. 8, ‘w’=wife; ‘h’=husband; ‘c’= child; ‘o’= officemate; ‘f’= friend). The numbers written on the edge represent the intimacy degree, though intimacy from A to B and intimacy from B to A can be of different degrees. For example, ‘VC_Human418’ views his intimacy degree with his wife ‘VC_Human419’ as only ‘1’; on the contrary, his wife ‘VC_Human419’, who is a housewife whose personal network only includes friends and husband, views intimacy with her husband ‘VC_Human418’ as a level ‘3’.

[3]Gephi can be download free from http://oss.infoscience.co.jp/gephi/gephi.org/.



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All personal networks similar to Fig. 8 comprise the entirety of the social network. In the personal network of each agent is recorded the name of human agent, the relationship type and the intimacy degree with acquaintances who appear within their network. The personal information about these acquaintances, such as sex, age, job, school, current location, etc., is also recorded in the computer model.

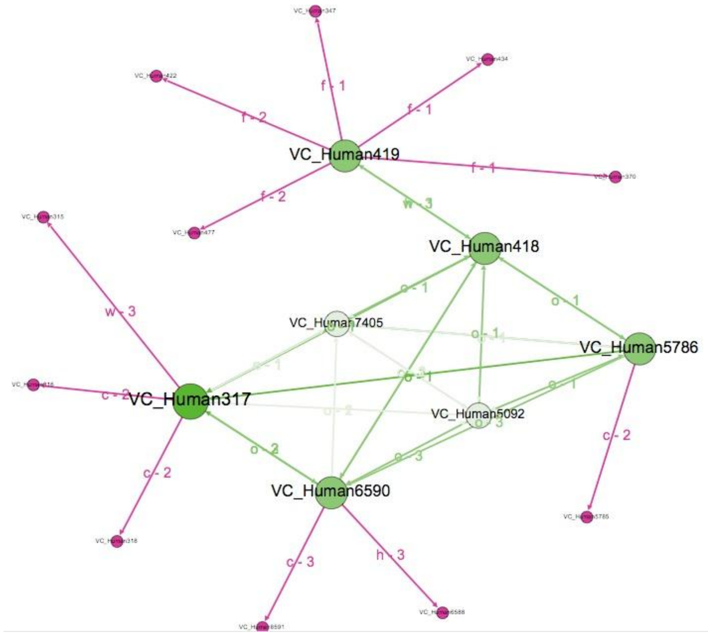


Fig. 8 Visualization of personal network

As an application of the model, it is applied to a pandemic immunization simulation; the model can also apply to other research fields by adding parameters and other modules. Moreover, we can also use the same social network generation method to construct social networks for other specific cities by changing the GIS and census data used in the model.

## IV. CASE STUDY APPLICATION OF THE MODEL

As an example of practical use for this social network model, we attempt to simulate immunization awareness diffusion phenomena under the social network of the city and changes in vaccination behaviors in the personal network of every human agent in this section.

According to an investigation[4] about the degree of recognition regarding immunization, recommendations from family or friends is one of the main influences, which affect the immunization awareness of humans. Such a phenomenon occurs because people are likely to be influenced by suggestions from their acquaintances. This phenomenon is also called "Subjective Norms" in the field of psychology. Therefore, to construct a pandemic immunization module based on the city model, it is essential to take into consideration the social network structure and all personal networks of each human agent in the city model.

### *A. Algorithms of Immunization Awareness Diffusion*

In the immunization setting, we assume that if referents in the personal network of an agent were vaccinated or recommend vaccination, the behavioral intentions of the agent are likely to be influenced. The potential referents included family members, workmates and friends. Therefore, we quantitate the influence from Subjective Norms (ISN) for agent 'i' according to the following equation by considering the influence of intimacy from the referents in the personal relationship network of agent 'i':

$$ISN(i) = \frac{\sum_{j}^{all \text{ vaccinated people in network of human i}} Id_{ij} \times Ld_j}{\sum_{j}^{all \text{ people in network of human i}} Id_{ij} \times Ld_j}$$

$Id_{ij} =$ intimacy degree from i to j ; $Ld_j =$ leadership degree of j

After calculating the influence from Subjective Norms (ISN) for agent 'i', we will introduce the way in which it influences immunization awareness of the agents in the model. To evaluate the effect from *ISN(i)*, we introduce a threshold parameter *'m'*,

[4]Japanese Immunization Awareness Investigation by Banyu Pharmaceutical co.ltd (April. 2010). http://www.msd.co.jp/newsroom/banyu-archive/pdf/product/product_news_0520.pdf.



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which assesses the possibility of collective behavior and the subjective norms. In the model, each agent holds a threshold *'m'* at the initial step; the initial value of *'m'* is decided by the 'frequency of doing the same thing with relevant people' from JGSS-2003. If '*ISN(i)>m'*, then people will obtain a vaccination. The vaccination behavior of each human agent at each iteration is illustrated in Fig. 9.

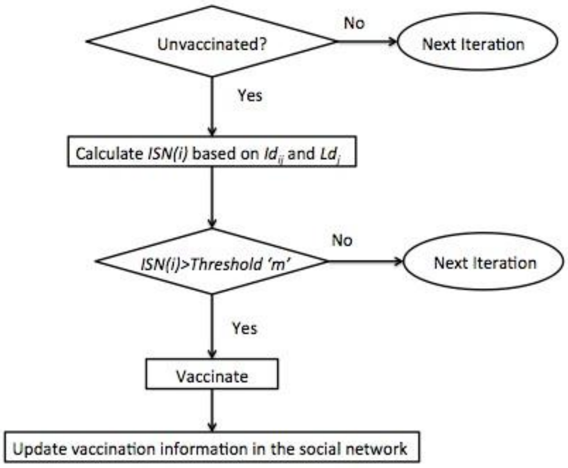


Fig. 9 Vaccination behaviour of each human agent at each iteration

*B. Micro Analysis of Vaccination Diffusion in Personal Social Network*

In the previous section, we generated a social network model which included 7584 human agents and all of their personal relationship networks. Based on the social network, we considered an algorithm of immunization awareness diffusion to simulate the pandemic immunization in the model. As a result, we provide an example of the immunization awareness change process in the personal network of a specific human agent: 'Human418', whose personal network has already been visualized in Fig. 8.

In the social network model, 'Human418' belongs to type Human(1,5,1,1,2): he is a man, a worker, 50 years old, and lives with his wife. The vaccination information in his personal social network is updated at every iteration. The diffusion process of his immunization awareness accompanies the vaccination information change in his personal network at every iteration; we record these changes as states. Fig. 10 illustrates its transformation (State1→ State2→ State3→ State4).

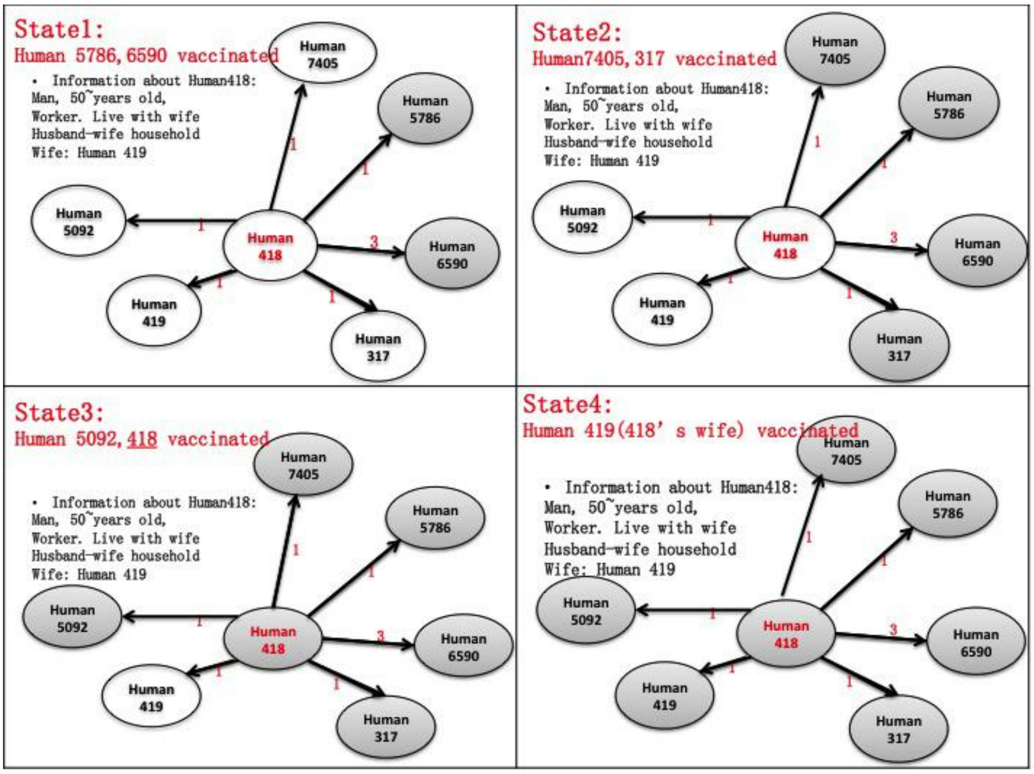


Fig. 10 Diffusion process of immunization awareness of Human 418



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## V. CONCLUSION AND IMPLICATIONS

This paper introduced an approach to generate a social network model by an agent-based simulation method, The Japanese General Social Survey provided us with a basis of reality regarding existing personal networks. This paper analysed the general characteristics of personal networks generated from the survey data and introduced a method by which to apply the results to a geographically based virtual city model. Moreover, by specifying the personal information (age, sex, job, etc.), geographic location, social interaction, and a series of entity rules of behaviour for each human agent, this paper generated a realistic model of a virtual Izu-oshima city by computer simulation. Finally, this paper applied the data analysis to the virtual city model to estimate the degree of intimacy in relationships between all agents in the model. Agents living in the virtual city and the relationships between them constituted the entire social network model.

This research applied data analysis of personal networks from a geographically-based virtual city model to generate a social network. Because this social network generation approach used statistical data, the results regarding city structure, population location and intimacy between human agents was able to match real statistics on a macro-level. On the micro-level, it is very difficult to compare the results with real data, because it is almost impossible to know all activities between acquaintances, which is one of the limitations of this approach. In the paper, we used this approach to generate a social network for a specific city: Izu-oshima. Because the number of agents, their home location and social institution were fixed in the model according to the real Izu-oshima city, the city population density and the relationships between agents approximated reality.

We analysed a social network on a national level, but we could not generate the entire social network of Japan in this research due to the following limitations: (1) technical limitations (such as storage capacity and computing power, etc.); (2) the geographically-based census and city survey are not complete for all cities in Japan; (3) the entire network and social structure of Japan are quite complicated. Therefore, we considered using a representative example to explain our approach: the example we generated was Izu-oshima. We chose this city because our research group had a long project with Izu-oshima so that we could obtain details of the city survey, which made the virtual Izu-oshima model convincible. Through an identical approach, we could also obtain social network models for other cities.

As an application of the constructed social network model, this paper introduced a pandemic immunization simulation and the vaccination diffusion phenomenon within the social network system. In the future, the generated social network has potential to be used in other sociological studies. In the future, we will consider other kinds of applications such as information spreading, diffusion of innovation, communication, etc., of the social network model in social simulations achieved by the agent-based simulation method.

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