Policy Decision Support System in Aging Society based on Probabilistic Latent Spatial Semantic Structure Modeling

Ayae Ide
School of computing
Tokyo Institute of Technology
Tokyo, Japan
ide.ayae@aist.go.jp

Yoichi Motomura
Artificial Intelligence Research Center
National Institute of
Advanced Industrial Science and Technology
Tokyo, Japan
y.motomura@aist.go.jp

Takao Terano
School of computing
Tokyo Institute of Technology
Tokyo, Japan
terano@dis.titech.ac.jp

Abstract

This paper analyzes a questionnaire survey data on elderly people in order to investigate regional characteristics of their living activities. For the purpose, we use Probabilistic Latent Spatial Semantic (PLSS) Modeling, which is integrated the two methods: probabilistic latent semantic analysis (pLSA) and Bayesian network (BN). First, we aggregate each individual's survey record by postal code; Second, we find characteristics of the region by pLSA; Third, we use BN to clarify factors of this regional disparity. From the study, we are able to identify critical information to support decisions for a manager in a local government: i) There is regional disparity in terms of social network; and ii) The regional disparity of social network will improve by neighborhood facilities. Such information will be of use for designing the super-aged society in the near future. We propose policy decision support system in aging society based on PLSS Modeling.

Introduction

As the aging will rapidly progress in worldwide, especially in Japan, which is the top of such a super aged society, the policy decision making in Japan is urgent study topic; for example, here will be the medical shortage caused by super aged society, and the increase in social security expenses. However, policy problems were thought to be difficult to deal with in existing social science. Policy problems are difficult to solve because of its complexity. As this complexity, there are four properties; 1)Comprehensiveness; policy problems involve various problems, 2)Reciprocity; policy problems conflict with other problems, economic development and environmental protection, 3)Subjectivity; Framing of policy problems are different depending on position and viewpoint , 4)Dynamics; Policy problems are changing everyday (Akiyoshi et al. 2015). For that reason, we need to construct model to understand structure and context of policy problems, and this model have to respond flexibly to changes of policy problems and reflect knowledge from multiple viewpoints and experts. That is, it is the model which is easy to understand the relationship between variables and reflect domain knowledge and new data. This research aims to policy decision support system for local government in aging society based on modeling which clarify regional disparities.
To realize this model, we applying computational social science techniques to a large scale survey study conducted by Japan Gerontological Evaluation Study (JAGES). JAGES are conducting large-scale questionnaire survey targeting more than 100,000 elderly people to uncover the current geographical status of living activities of elderly people. With this questionnaire, it is possible to acquire data on elderly people from a multifaceted viewpoint such as body, psychology, society. One of main objects in this project is to clarify regional health disparity and regional characteristics in order to support policy making of local governments.

Currently, data analysis using spatial data is increasingly important in the context of policy decision making. Spatial data are used in various policy fields, and in the field of medical policy, it is applied to problems such as factor analysis of mortality rate and correction of regional disparities. In the mid-19th century, J. Snow created a map to find out the spatial ubiquity of the distribution of cholera patients in London (Snow, John 2015). This is a method of space clustering and has been developed in a field called Spatial epidemiology. Time, person, and place are 3 main epidemiologic variables (Pfeiffer, Dirk, et al. 2008), in particular, place is the most important variables in the context of policy decision making. In the scene of policy, municipalities have intervention at regional level. In this research, we use the postal code attached to the questionnaire data as primary key.

Based on this background, this paper analyzes the questionnaire data with recent plural machine learning techniques and simulates policy effect at regional level. First, we apply a clustering technique to extract postal code groups. Second, we find characteristics of the region by and question item groups via probabilistic latent semantic analysis (pLSA). Third, we apply bayesian network (BN) to the data to understand relations among many variables. Based on the obtained model, we carry out causal reasoning in regional health disparity.

The rest of the paper is organized as follows: In Section 2, we describe the data and method in order; in Section3, we give investigation results of each method; Section 4 gives discussion of the study, and finally, Section 5, we give some concluding remarks.

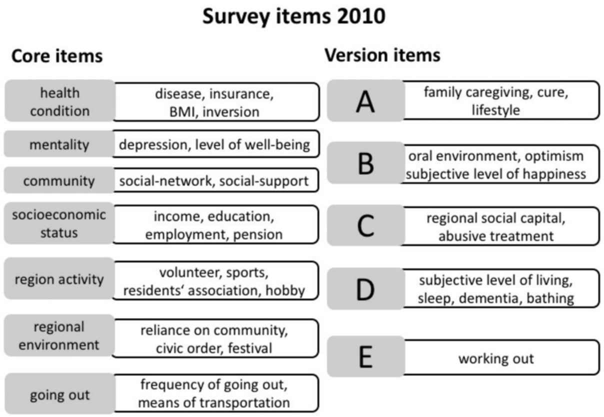

Figure 1: JAGES question items

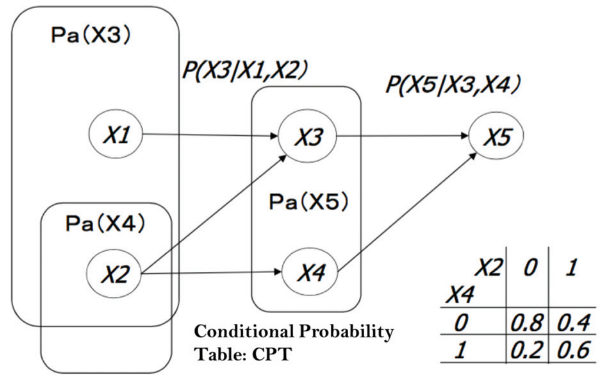

Figure 2: Bayesian network

Data and Methods

Data

The target data of this analysis is JAGES 2010-2013 cohort data which is 2010 cross-sectional data combined with certification of long-term care need in 2013. This is tracking data of the respondents in 24 municipalities targeted for the 2010 survey. There are some variables in certification of long-term care data, for example, dead, dementia and the level of care needed. JAGES 2010-2013 cohort data has 74264 records and 53801 records have postal code.

The question items in the questionnaire consist of core items and version items. Core items are items common to all respondents and five types of version items of the A to E version are equally attached to the core items. The outline of questionnaire items is shown in Fig.1.

Methods

pLSA(Hofmann, Thomas 1999) has been proposed as a method of document classification and is one method of text clustering. In this method, we assume that word w in document d is generated via latent variable z. In the likelihood maximization by the EM algorithm, the latent variable $z \in Z = \{z_1, ..., z_k\}$ is attached to the co-occurring data. In this study, we assume that the postal code w_i responds to the question answer d_i via the latent variable z_k, and extracted postal code groups and question item groups with similar responses in the questionnaire data. Co-occurrence frequency is $n(i, j)$. The joint probability is expressed by the following equation.

$$P(w_i, d_i) = \sum_k P(w_i|z_k)P(d_i|z_k)P(z_k) \qquad (1)$$

After that, $P(w|z), P(d|z), P(z)$ are calculated by EM algorithm which maximizes the following log likelihood function.

$$L = \sum_i \sum_j n(i, j) \log P(w_i, d_i) \qquad (2)$$

pLSA can maximize information content by EM algorithm so that dimension reduction, which has less loss of information content, can realize in the resulting segment. Analysis that extracted latent classes using pLSA is effective for big data but it does not express explicitly what the extracted latent class represents, so it is difficult to understand the meaning of that latent class intuitively. It is a big problem when manually analyzing after extracting latent classes. Therefore, we consider a probabilistic latent semantic modeling that can model latent classes extracted by pLSA, and furthermore, relationships between latent classes by Bayesian network. By modeling relationships with the explanatory variable, there is an advantage that the latent class which was intuitively difficult to understand can be characterized by the related explanatory variable.

The Bayesian network (Pearl, Judea 1985) is one of graphical model that enables prediction of events and reasonable decision making.The model created can be represented by network graph. The product of simultaneous probabilities among the variables shows the simultaneous distribution of the model. In addition, by using the probabilistic reasoning algorithm, posterior probability calculation, sensitivity analysis can be executed(Motomura 2009).

A Bayesian network is a model in which a qualitative dependency relationship among multiple random variables is represented by a graph structure and a quantitative relationship between individual variables is represented by a preceding conditional probability as Figure2. This is a probabilistic model defined by random variables and the conditional dependency between random variables and its conditional probability. A variable is a node, a dependency relation between variables is represented by an oriented link extending in the direction of the variable resulting from the cause, a node that comes before the link is called a child node, and a node under the link is called a parent node. For example, the dependence relation between random variable X_i and X_j is represented by directed rink X_iX_j. X_i is parent node, and X_j is child node. When we assume that the set of parent nodes $\pi(X_j) = \{X_1, ..., X_i\}$ with child node X_j. The dependency relation between X_j and $\pi(X_j)$ is quantitatively expressed by the following conditional probability.

$$P(X_j|\pi(X_j)) \tag{3}$$

Furthermore, for each of the n random variables $X_1, ..., X_n$, in the same way as a child node, the simultaneous probability distribution of all the random variables is as below.

$$P(X_1, ..., X_n) = \prod_j P(X_j|\pi(X_j)) \tag{4}$$

The Bayesian network is a modeling based on discontinuous probability distribution in which X - Y space is discretized according to the conditional probability table and individual probability values are assigned. However, we apply bayesian network to big data, the number of states of the discrete random variable becomes enormous. For that reason, the size of the conditional probability table becomes huge and frequency distribution becomes sparse, so that model construction becomes difficult. To solve this problem, it is necessary to cluster the state to an appropriate granularity beforehand(Ishigaki et al. 2010). Therefore, clustering by pLSA as prior processing can prevent from frequency distribution becoming sparse(Murayama et al. 2015; Hirokawa et al. 2015). In other words, a structure model corresponding to big data is constructed by classifying the elderly or the region into latent segments with pLSA and constructing a Bayesian network that estimates the probability of belonging to the latent segment from various variables. In this research, we added aggregation by postal code as data processing. We called this method Probabilistic Latent Spatial Semantic (PLSS) Modeling.

Results

pLSA

We extracted latent segments from JAGES dataset aggregated by postal code by using pLSA. The total number of postal codes is 2133.The number of latent class was determined based on AIC(Akaike 1987). There is an initial value dependence because EM algorithm is used for the likelihood calculation of pLSA. Thus, by changing the initial value 5 times, the latent class was increased from 4 to 45 and the minimum value at each cluster number was compared. The figure 3 indicates AIC scores. As a result, since AIC has the minimum value when K = 25, the number of clusters 25 was selected. PLSA is a method for maximum likelihood estimation of topic model so that all variables belong to all clusters and the degree of affiliation is given by probability. We assigned postal codes and question answers to clusters with the highest affiliation probability.In figure 4, this is scatter plot of postal codes in which the vertical line shows $P(w_i|z_k)$ and the horizontal one z_k. As can be seen from the figure, postal codes are distributed mainly in Z003 and Z009 and Z025. Moreover, most of affiliation probabilities is less than 0.5 and it's meaning variables belong to more than one cluster at the same time. Figure 5 and 6 shows affiliation probabilities of all postal codes and question answers in each cluster. All clusters have different distribution of affiliation probability.

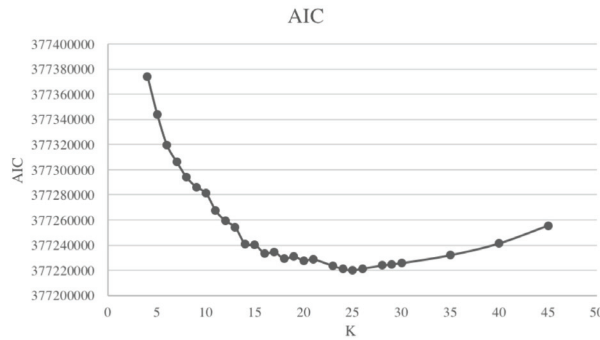

Figure 3: AIC scores

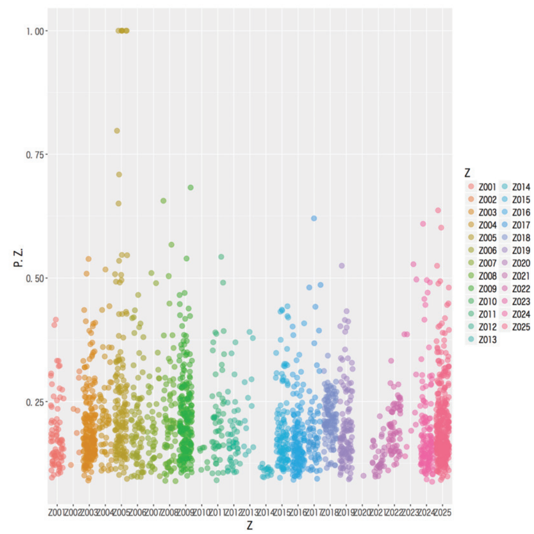

Figure 4: Scatterplot of postal codes with highest affiliation probability

We take these three main clusters for instance. Figure 7 shows top 10 question answers with the highest affiliation probabilities. The columns of question answers are color-coded, in particular, answers about hobby are green, answers about near facilities are blue, and answers about isolation are red. Similar answers are listed for each cluster, and the potential trends of clusters can be interpreted as follows. Z003 and Z009 are the areas where hobby activities are active and no isolation, on the other hand, Z025 is the area where people lacked social and community ties.

We consider Nagoya city which has the largest number of respondents among subject municipalities. First of all, in each 16 wards constituting Nagoya City, the number of postal codes belonging to each 25 clusters was counted. Then, considering the cluster with the highest postal code distribution as the cluster representing the administrative district, a choropleth map is created and shown in figure 8. As shown in figure 8, the representative clusters are equal in the neighboring area. Hence, it was confirmed that the ten-

Figure 5: Affiliation probability of postal codes

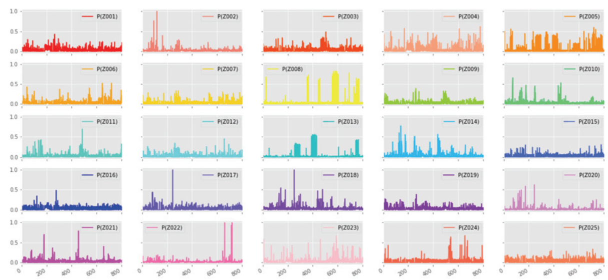

Figure 6: Affiliation probability of question answers

Z003			
P(w/z)	Postal code	P(d/z)	question answers
0.538	4470001	0.487	Hobby (Painting)
0.508	4640054	0.357	Hobby (Golf)
0.435	4620869	0.341	Receiving pension (Private pension)
0.412	2770083	0.340	Frequency of participation in sports groups(Weekly, Monthly)
0.410	2770853	0.339	Hobby (Instrument Performance)
0.408	4670045	0.337	Hobby (tea ceremony・flower arrangement)
0.402	4610021	0.329	Hobby (Gym・Tai Chi)
0.393	4650074	0.321	What is the region for you (etc.)
0.389	4770035	0.310	Hobby (Haiku・Tanka・Poetry)
0.369	4660033	0.309	Dinner companion (friends)

Z009			
P(w/z)	Postal code	P(d/z)	question answers
0.683	4670035	0.393	Facilities within 1 km from house (Slope and Steps)
0.539	4520838	0.324	Hobby(PC)
0.470	0710251	0.316	Facilities within 1 km from house (Park and Promenade)
0.466	4640836	0.315	Facilities within 1 km from house (Attractive scenery and buildings)
0.447	4570864	0.292	Years of school education (over 13 years)
0.438	4650044	0.288	Hobby (hill climbing)
0.425	4680029	0.265	Hobby(Go・Shogi・Mahjong)
0.423	4670062	0.255	Hobby(Photography)
0.417	4640856	0.237	Drinking companion (wife・husband)
0.403	4650027	0.189	Drinking frequency (3-4 per week、1-3 per month)

Z025			
P(w/z)	Postal code	P(d/z)	question answers
0.636	4540868	0.300	Friends or acquaintances frequently meeting (None)
0.601	0711441	0.285	Hobby (Pachinko)
0.524	4530846	0.271	Frequency of meeting with friends (None)
0.494	4530861	0.227	tobacco (smoking cessation within 4 years)
0.489	4540824	0.223	Frequency of eating vegetables and fruits (2-3 per week)
0.481	4580916	0.215	Annual income for the entire household (200-250 thousand)
0.449	0711454	0.206	Frequency of meeting with friends (1-3 per year)
0.446	4570813	0.206	Number of friends met last month (1-2 person)
0.419	4610031	0.201	Frequency of participation in hobby groups (None)
0.408	4630803	0.196	Hobby (Fishing)

Figure 7: Postal codes and Question answers with the top 10 highest affiliation probabilities

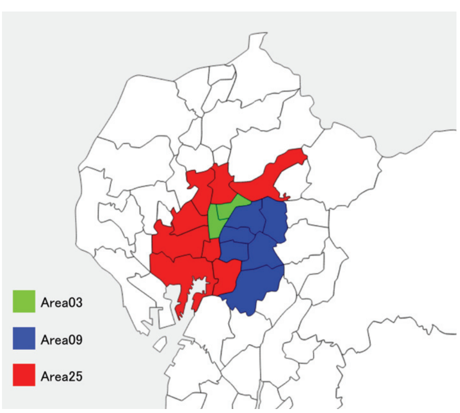

Figure 8: Cluster distribution in Nagoya city

dency of answers is similar when the residential areas are located nearby. There is a high possibility that there is a correlation between the response tendency of the elderly and the resident area. The results of figure 7 and figure 8 suggest there is regional disparities in terms of social network.

Bayesian network

In this research, we used Bayonet (Motomura 2003) to create a Bayesian network. The determination of the graph structure of the Bayesian network can be determined by Greedy algorithm that searches for the optimal local tree for each child node. We build Bayesian network by the procedure 1) child nodes are defined, 2) candidate local trees are given for each child node, 3) conditional probability is determined for each local tree, 4) an optimal local tree is searched for Greedy for each child node. In the procedure of 4), when choosing a tree, we select the candidate set given in advance by the selection criterion (MDL, AIC) which takes into consideration the likelihood and the complexity of the model. Extracting regional questions out of all questions, we constructed a bayesian network with the answer and the variables belonging to the above three clusters in figure 9. This questions are about the change in their area in the past 3 years and about the environment within 1 km from their house. In this bayesian network, the upstream is occupied by neighboring facilities, it propagates to the change of the area, and eventually leads to cluster affiliation. This result suggests that neighborhood facilities affect regional change, regional change affect regional disparity. By executing probabilistic reasoning on this bayesian network, the influence

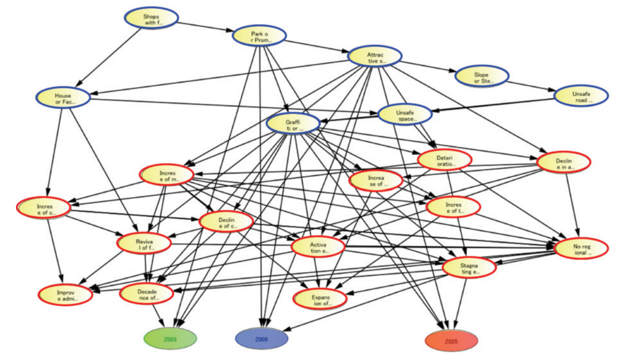

Figure 9: Bayesian Network about regional characteristics

degree between nodes can be quantitatively calculated.

We focus on the node of Increase of local communication and activity. There are three parent nodes linked to this node,“Houses and Facilities that you can drop in casually within 1 km from your house”, “Increase of people moving in”, “Deterioration in security”. By giving numerical value into each node and comparing the prior probability with the posterior probability in figure 10, it increases from 3.7 percent to 19.8 percent by regional intervention. In other words, if you increase the number of homes and facilities that you can drop in easily, promote an increase in the number of people moving in and improve the public safety, it can be expected that the local community will be revitalized. As this inference on the top down, by giving numerical value to the parent node on the Bayesian network and looking at the probability transition of the child node, it is possible to deduce what kind of result will occur with a certain probability under a certain hypothesis.

On the other hand, by giving numerical value to a child node and looking at the probability transition of the parent node at the bottom up, the most likely hypothesis can be obtained when the result is given. As shown in figure 11, when the result of No in “Expansion of income gap” is obtained, the probability of Sometimes in “Graffiti or Garbage” decreased. Moreover, the probability of No in “Increase of unwaged” and “Increase of people moving in” has increased. This result suggests graffiti and garbage in the neighborhood and the increase of unwaged and people moving in are factors of expansion of income gap. In this way, it is possible to use the Bayesian network as a hypothesis construction.

Discussion

Importance of social capital

This study shows the presence of disparity of social network. Epidemiological studies have concluded that people who are socially integrated live longer(House, James S et al. 1988). Berkman’s study have shown that the people who lacked social and community ties were more likely to die than those with more extensive contacts.

The age-adjusted relative risks for those most isolated when compared to those with the most social contacts were 2.3 for men and 2.8 for women(Berkman, Lisa F et al.1979).

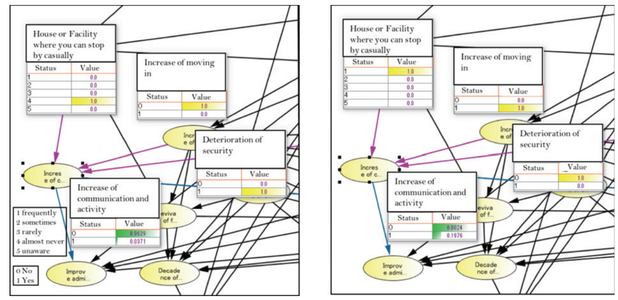

Figure 10: Bayesian Network Infer : Top-Down

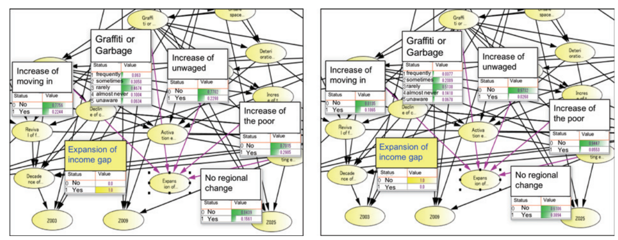

Figure 11: Bayesian Network Infer : Bottom-Up

These studies show the evidence that the social cohesion enhances longevity.Robert Putnam defined social capital as features of social organization, such as trust, norms, and networks, that can improve the efficiency of society by facilitating coordinated actions(Putnam, Robert D et al. 1994).

There are three plausible reasons why social capital affect individual health(Kawachi et al 1999; Kawachi et al. 1997; Kawachi et al. 1997). According to Kawachi’s study, (1) social capital may influence the health behaviors of neighborhood residents by promoting more rapid diffusion of health information, increasing the likelihood that healthy norms of behavior are adopted (e.g., physical activity), and exerting social control over deviant health-related behavior, (2)neighborhood social capital may influence health by increasing access to local services and amenities, (3) neighborhood social capital may influence the health of individuals via psychosocial processes, by providing affective support and acting as the source of self-esteem and mutual respect.

In Japan, we always hear news about dying alone and social isolation of the elderly. On the other hand, Japan also have communities where there are strong connections through neighborhood associations and local governments. Local governments have the potential to greatly contribute to Japan’s aging society by focusing on social capital. As part of that, this study suggest the method for regional characteristics extraction and decision support for regional intervention and showed the analysis results.

Social capital and Regional environment

From the view of social capital, there is hypothesis that explains the results of this study. From figure 7 and figure 8, the east side of the city is Z009, where the cluster has good environment, and seem to be no isolation because drinking with companion. On the other hand, the west side of the city is Z025. This cluster is the area where people lacked social and community ties. Nagoya city has large scale green parks with forest in the east side. For example, there are Higashiyama park and Heiwa park in Tikusa ward, Obata green tract of land in Moriyama ward, Makinogaike green tract of land in Meito ward and Odaka green tract of land in Midori ward. All of these parks are in the east side of Nagoya. The core of the city is the central part of Nagoya, where commercial facilities and office buildings were build. With figure 9, three cluster: Z003, Z009, Z025 have common parent node in the most upstream, it is just "Parks and promenades suitable for exercise and walking." Here is the hypothesis that the fact that there are parks in the neighborhood gives rise to social capital disparity. Ariane L's study shows psychological benefits for park users that arise from the proximity of natural environments(Bedimo-Rung, Ariane L et al. 2005). Other study (Godbey, Geoffrey, and Michael Blazey 1983) has shown that older adult park users who participated in moderate aerobic activity were in a better mood after visiting the park. From the perspective of public health, it would be beneficial to add parks and encourage social capital.

Policy Decision Support System in Aging Society

Gerontechnology is defined as interdisciplinary academic and professional field combining gerontology and technology(Bouma, Herman et al. 1992). This field not only supports the elderly but also will develop into a core industry in Japan. In China, the number of elderly people will exceed 200 million in 2025. Japan is expected to help asian countries and promotion of economic growth by gerontechnology.

Policy problems in aging society are also needs solution by Gerontechnology. Policy problems are complex structures involving various factors so that there is high possibility of misjudging the problem in the conventional field-specific ways. However, PLSS Modeling reflects the complexity of policy problems. As stated in introduction, there are difficulties in policy problems: 1)Comprehensiveness; BN capture the relationship of many variables without being bound by field-specific views. Moreover, BN reflects knowledge from multiple viewpoints and experts as prior distribution. 3)Subjectivity; The relationship between variables is visually clear and we share the frame of problems. 4)Dynamics: BN respond flexibly to new data and changes of policy problems. PLSS Modeling based on JAGES data enable local governments to construct hypothesis about values and needs of elderly people. Longitudinal data integration and analysis will improve prediction accuracy. JAGES aims to make smart aging society by artificial intelligence and develop health care simulation science. Figure 12 shows the framework of data platform in aging society. PHR means Personal Health Record, which is a collection of health-related information that is documented and maintained by the individual it pertains to. It is necessary to constantly reflect social feedback to the model without separating modeling and application using model. Therefore, we should follow the cycle as Figure 13. By continuing this cycle, it is expected that system will be established to continuously calculate the characteristics of diverse elderly people and utilize them as useful knowledge for society. Sharing this system will help realization of new social infrastructure in aging society.

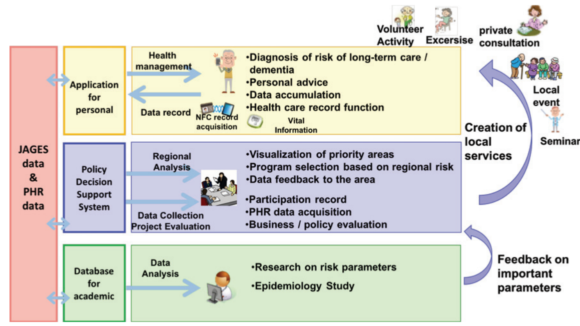

Figure 12: JAGES and PHR data platform in aging society

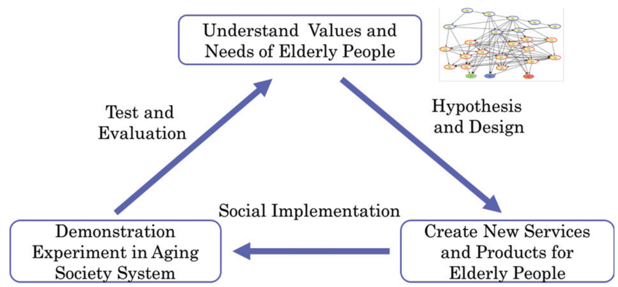

Figure 13: Cycle for solving problems in aging society

Conclusion

The paper has described Probabilistic Latent Spatial Semantic (PLSS) Modeling which is integrated probabilistic latent semantic analysis and bayesian network to uncover the current geographical status of living activities of elderly people. Finally, this paper proposed policy decision support system to implement PLSS Modeling in the real world.

We have clarified the latent regional characteristics and the factors of regional disparities from the elderly questionnaire data. We also mentioned what kind of intervention the municipal government should take to solve regional disparities. It became clear that 1)there is regional disparities in terms of social network, 2)neighborhood facilities affect regional disparity, 3)the local community will be revitalized by increasing the number of homes and facilities that you can drop in easily, promoting an increase in the number of people moving in and improving the public safety.

In the future, there is need to comparative controlled study to certify causality. By using the results of clustering regions, we are able to compare regions without intervention and with intervention in the same cluster. JAGES is engaged in intervention by holding local events. We plan health tracking such as blood pressure measurement at these events for model evaluation.

Our remaining works include i) undersampling data before constructing BN to improve the accuracy of prediction of health status; ii) time series data analysis using other year's survey data; iii) intervention trial to certify causality; These future works might help local government to improve social capital and health status.

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