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(出版者 / Publisher)
法政大学大学院情報科学研究科

(雑誌名 / Journal or Publication Title)
法政大学大学院紀要. 情報科学研究科編 / 法政大学大学院紀要. 情報科学研究科編

(巻 / Volume)
10

(開始ページ / Start Page)
1

(終了ページ / End Page)
6

(発行年 / Year)
2015-03-24

(URL)
https://doi.org/10.15002/00011607

From Increasing Personal Data to Growable Cyber-I's Modeling

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***Abstract*—Cyber-Individual (Cyber-I), is a counterpart of Real-Individual (Real-I) in cyberspace, which aims to create a unique, digital and comprehensive description for every real individual to support various personalized services and applications. A Cyber-I is able to gradually approximate to its Real-I, and the approximation accuracy can be continuously improved by collecting, processing and utilizing personal data related to its corresponding Real-I. One of basic characteristics of the personal data is the continuous increase of data types and amount due to wide uses of smartphones, sensors, and other devices as well as software tools. Such increasing personal data offers the possibility to make growable Cyber-I modeling for each user. This research is mainly focused on the initialization and growth of the Cyber-I modeling. An initial Cyber-I model is a beginning description about an individual, which is made based on the basic data generated in the Cyber-I's birth stage. A growing model is one that can grow up to become bigger, higher or closer for a Cyber-I to successively approximate to its Real-I's states, behaviors and characteristics. This paper discusses in details on how the initial models and growing models are built and work. A system prototype to support the model initialization and growth is illustrated, and a case study to concretely show the growable modeling is also given.**

Keywords—Cyber-I; personal data; user modeling; preference; profile; initial model; growing model; approximation

I. Introduction

With rapid advances of computing and communication technologies, we are stepping into a completely new cyber-physical integrated hyper world with digital explosions of data, connectivity, services and intelligence. As individuals facing so many services in the digitally explosive world, we may not be aware of what are the most necessary or suitable things. Hence, the appearance of Cyber-I, short for Cyber-Individual, is a counterpart of a real individual (Real-I) to digitally clone every person [1] [2]. The study on Cyber-I is an effort to re-examine and analyze human essence in the cyber-physical integrated world in order to assist the individuals in dealing with the service explosions for having an enjoyable life in the emerging hyper world.

In order to build a Cyber-I, a fundamental problem is to figure out how a Cyber-I can approximate to its Real-I's characteristics and even mind [3]. The study of Cyber-I modeling is the most important way to tackle this problem. Obliviously, a comprehensive and sophisticated Cyber-I model cannot be built at once because there is no enough personal data in the initial modeling stage. Fortunately, more and more personal data can be collected by means of various software tools and ubiquitous devices such as smartphones, sensors, wearable devices, and so on. Such personal data comes increasingly and thus offers a possibility to make the models grow as if the creature in the nature needs nutriment to grow and the models of Cyber-I can grow with the digital "nutrition", namely, increasing personal data.

After more and more personal data becomes available, the basic issue is how to generate Cyber-I's initial models and make the models growable. The ultimate goal is for the growing models to successively approach to or become more similar as individual's actual characteristics along with increasing personal data from various sources covering different aspects. The focus of this research is on the initialization and growth of Cyber-I's models. The initial models are generated based on the personal data acquired in a Cyber-I's birth stage, while the growing models are built with the personal data continuously collected after the birth. We proposed three mechanisms for Cyber-I modeling to enable the models growing bigger, higher and closer successively to its Real-I.

The rest of the paper is organized as follows. In section II, the related work about life logging and user modeling are described. In section III, we give an overview of our growable Cyber-I's modeling, discuss the categories and features of increasing data, and show the data collected for our research. Section IV presents different ways to generate initial Cyber-I's models. Section V explains the growth in Cyber-I modeling. Section VI first introduces our system prototype for growable modeling and then shows a concrete case study. A summary of this research and a brief description of future work are given in the last section.

II. Related Work

User models are also known as user profiles, personas or archetypes. They can be used by designers and developers for personalization purposes so as to increase the usability and accessibility of products and services [4]. With the development of personalized systems, like e-learning systems, a lot of personal data can be collected. In order to find some personal features to give appropriate advices or recommendations, the user model should be established in service systems [5]. However, many such kind of user models is application-specific or service-specific which cannot be used by other applications/services [6]. To overcome this barrier of the user models between different applications, a generic user model system (GUMS) was proposed to support interoperability among different user modeling systems [7] [8]. The GUMS is able to exchange contents of user models, and use the exchanged user's information to enrich the user experience. Life logging is utilized to automatically record user's life events in digital format. With continuously capturing contextual information from a user and the user's environment, personal data increases fast and becomes huge. The most of lifelog systems are putting more emphases on personal data collection, storage and management [9]. Lifelong user modeling is trying to provide users such models accompanied with users' whole life [10]. This idea or vision is attractive, but no general mechanism has been made and no practical system has been built yet. Lifelong machine learning (LML), received great attention in recent years, is to enable an algorithm or a system to learn tasks from more domains over its lifetime [11].

All technologies in user modeling, life logging, lifelong user modeling and LML are closely related to Cyber-I modeling. However, our emphases are modeling a human beyond a user and building growing models to approximate the human along with increasing personal data.

III. CYBER-I MODELING AND PERSONAL DATA

As we said previously, a Cyber-I is a counterpart of Real-I in the cyber world. The process of building Cyber-I's models is not static, and has to be dynamic, i.e., gradually approximating to its Real-I. Figure 1 shows the process of Cyber-I modeling from personal data, initial models to growing models.

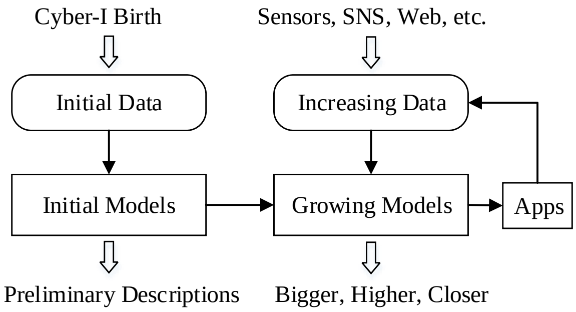

Fig. 1. Overview of Cyber-I modeling

The collection of personal data, including the initial data generated in the Cyber-I birth stage, is to act as a beginning of the Cyber-I's follow-up growth along with coming data, namely, increasing personal data. By means of various Web, ubiquitous sensing and other technologies, lots of personal data can be captured. Based on available sets of the initial data, different kinds of initial models will be generated. The initial models, namely preliminary descriptions about Cyber-I, will act as seeds for models' growth. The initial models are generated from initial data including the user's basic information, profile and preferences, which will be discussed in Section IV. By means of continuously collecting and integrating scattered and increasing personal data, models will grow for becoming bigger, higher and closer. The growing models mean the ones that are able to grow to successively approach to or become more similar as individual's actual features, which will be explained in details in Section V. The Cyber-I models can be used to build personalized services and evaluate the generated models for improving growth. Meanwhile, the applications can generate new data to make further data increase.

Personal data (PD) means any information concerning a single person that can be identified, which can be obtained from various sources covering different aspects. And the personal data generated from devices, sensors or applications can become progressively greater in size or amount with time going by, so such data on the whole is called increasing personal data. Personal data may increase in two ways, (1) increasing in quantity, i.e. the data from the same source comes more and more, and (2) increasing in types, i.e. the new types of data are added from other sources. There are four categories of increasing data: continuous, periodic, aperiodic and burst as shown in Fig. 2.

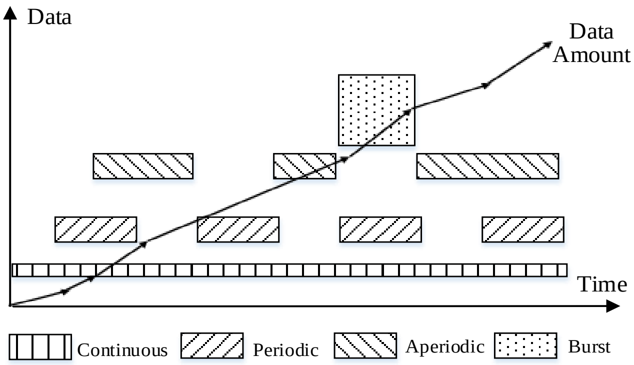

Fig. 2. Catergories and features of increasing personal data

Continuous data means data coming for a constant period of time without interruption like audio and video. Periodic data occurs or recurs at regular intervals, such as GPS data taken in a periodic time interval, say every 10 minutes. Aperiodic data is generated in irregular occurrence, for instance, when a user posts tweets, the data comes almost randomly. Burst data refers such data coming suddenly and with a relatively big amount in short time. One example is that news on the Web about a particular event may increase extremely fast. Along with time going on, the total amount of personal data may become more and more, namely, personal big data. In this research, the following types of personal data have been collected, as shown in Table. I.

TABLE I. COLLECTED DATA AND FEATURES

Data Source	**Data Type**	**Data Category**	**Data Use**
Cyber-I's Birth	Basic Info	--	Initial Models
Facebook/QQ	Profile	--	
Multiple Choices	Preference	--	
Twitter	Tweets	Aperiodic	Growing Models
Web	Web Pages	Aperiodic/Burst	
Browser	URL History	Aperiodic	
Jawbone UP	Movement	Continuous	
GPS	Location	Periodic/Aperiodic	
Manic Time	App/Act Log	Aperiodic	

IV. The Initialization of Cyber-I Model

Initial model is a Cyber-I beginning model which is generated from the user's basic information, preferences and profiles. The initial model stands for a beginning description or template, and provide a well-grounded foundation for the model to grow just as the importance of a seed to a tree. IM-C (Initial Model from Core Data) is the seed of Cyber-I model. However, only one method of initialization is not enough, just like the nature world, different "seeds" have to experience different stages of incubation to Cyber-I initial modeling. Various users have different attributes and possess distinct personal data. Therefore, different methods are supported in the initialization of Cyber-I modeling. As shown in Fig. 3, three kinds of basic initial model IM-C, IM-S and IM-P could be generated at different situations, while the IM-CS, IM-CPS and IM-CP is the combinations of the former three initial models.

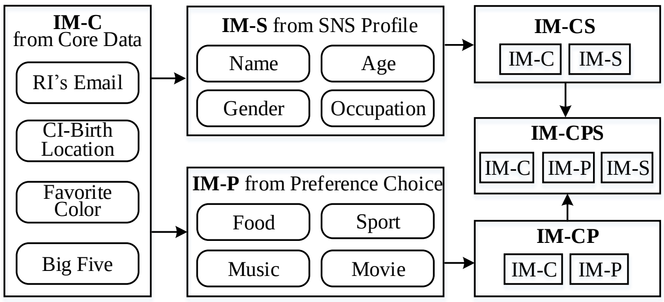

Fig. 3. Different Initial models and their combinations

A. Initional Model from Core Data (IM-C)

Core initial data is generated in the process of the Cyber-I's birth, including the email of Real-Individual (RI), birth location (inferred from IP address), favorite color and Big Five personality traits (through personality test questionnaire). In the Cyber-I birth stage, an email input by a user could serve as a bridge between Real-I and Cyber-I for their information interaction. Meanwhile, the current IP-address information is automatically recorded, which can be processed and calculated into a rough location. After that, a preference choice is necessary to reflect the user's inner property at an aspect. In this research, we start from the simple color preference, which may not be sensitive for someone's privacy concern and generally speaking, everyone has his/her own favorite color. Besides, it is relatively easy to make color choice and a user might feel pleasure to make his/her own color preference. Finally, the user is asked to fill up a Big Five questionnaire. These five factors provide a rich conceptual framework for integrating all the research findings and theory in personality psychology. After collecting and processing the above data and storing it into the personal database, the seed of Cyber-I model is generated.

B. Initional Model from SNS Profile (IM-S)

Online social networking service (SNS) is a great way to find out more about a user, which allows anyone with an email address to create a profile with pictures and a variety of specific personal information. The SNS profile plays an important role during the initialization of Cyber-I modeling since it contains some context information that is able to be utilized in the future. For instance, taking a user's age, occupation or hometown into consideration will better locate the user or provide the user with better services. IM-S is a kind of initialization method if a user is willing to provide his/her account. After the overall consideration of the favorite SNS website (Facebook, LinkedIn, QQ weibo), we found that the four elements *name*, *age*, *gender* and *occupation* are compulsory. Therefore, we take advantage of them as the mandatory parts to generate the IM-S.

C. Initional Model from Preference Choice (IM-P)

The psychological research has proved that the recognition of a user preferences could reflect something deep inside the user, such as characteristics or traits. And such preferences could also influence the selection and instantiation of the action that lead to achieve the user's target. In this research, we suggest a user choosing the other optional preference choices, which are *Foods*, *Sport*, *Movie* and *Music* as shown in Tab. II. If a user is willing to choose those, the model will contain more aspects of the user from different aspects. We make a user interface where six options for each choice are offered and they could also input by themselves if there is no appropriate answer for them. IM-P is composed of four aspects about favorite foods, sports, music and movies. IM-P could also be a start to generate a higher level description about the user, which is one kind mechanism of growable modeling and will be explained in the next section.

TABLE II. Preference Choices

Preference	Choices
Food	salty, sweets, spicy, sour, meet, vegetable, etc.
Sport	swimming, athletics, team/person ball, outdoor,fight, etc.
Movie	animation, comedy, adventure, action, romance, war, etc.
Music	jazz, classical, folk, rock, pop, rap, etc.

There are three ways of combinations, IM-CS, IM-CP and IM-CPS. If a user is willing to input his/her SNS account and choose preferences of different aspects, we can know more properties about the user so that more exact information could be offered to him/her in personalized applications. Meanwhile, the applications can also generate some additional new data, which help the models to grow.

V. The Growth of Cyber-I Model

A growable model means the one that is able to successively approach to individual's actual features, along with increasing personal data from various sources. After analyzing the features of Cyber-I model and comparing between Cyber-I model and human brain, we put forward modeling mechanisms for Cyber-I models to become bigger, higher and closer. The general modeling process is illustrated in Fig. 4. The data reserved in personal database is added to our modeling module, and data classifier is activated to make a classification and add a class Id. A user can see data list and select a function from processor base to process the data. Afterwards, data processor generates the processed results. Model controller is utilized to (1) examine the existing models, (2) make the model grow driven by time, user, or event, and (3) choose a corresponding function to grow bigger, higher or closer. In this way, the new generated grown model is reserved in model database for next cycle of growth.

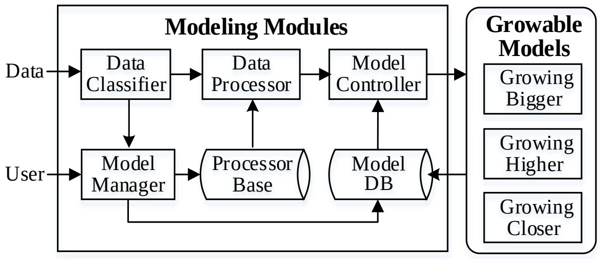

Fig. 4. Modeling modules for growing bigger, higher and closer

A. Growable Modeling for Becoming Bigger (GM-B)

Growable modeling for becoming bigger, short for GM-B, has two meanings. One is that the model could grow to cover more aspects of the individual just as a tree will grow with more branches. The other is that the model grows finer in one specific aspect by showing more exact and more detailed descriptions. The process of growing bigger is shown in Fig. 5. Suppose data D_1, D_2 and D_3 are three kinds of data coming from different sources. After analyzing D_1, D_2 and D_3, and extracting the corresponding information, it is found that D_1 and D_2 cover the aspects A_1 and A_2, which are not included in the present model. As a result, the model controller adds A_1 and A_2 to the current model. D_3 contains some detailed information that is related to A_2, therefore A_2 will extent to A_{21} and A_{22} with the information extracted from D_3. In this way, the model has grown with more aspects and finer in some specific aspect. Whether generating more aspects or extending the exist aspects to a deep level is decided by the model controller and the current model. For example, one of the keywords “Kobe Bryant” is contained in user’s tweet. After analyzing by some text mining tool, it is found that “Kobo Bryant” is a basketball player so that this aspect could be classified under basketball. If the aspect of basketball doesn’t exist in the current model, then the aspect of basketball is added to the model. If it exists, the user’s favorite basketball player may be added under the aspect of basketball.

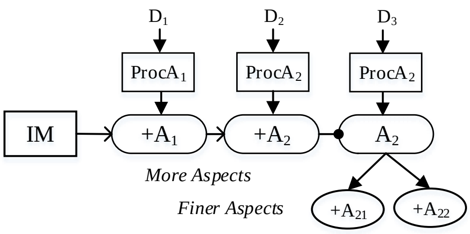

Fig. 5. Growable modeling for becoming bigger

B. Growable Modeling for Becoming Higher (GM-H)

Growable Modeling for becoming to a higher level means an abstract refinement of description based on Real-I’s interest, behavior and trait. As shown in Fig. 6, four levels are defined in our modeling. Level 0 is the *data level*, which is composed of different data coming from initial data (Cyber-I birth) and increasing data (Sensor, SNS, Web, application, etc.). Level 1 stands for *state level* that can be considered as the description of a user. For instance, a user likes yellow, basketball and action movie. Level 2 is the behavior level in which different aspects are combined to generate the basic feature or behavior. Level 3 is *characteristic level* that describes a user’s characters such as his/her high extraversion. As time goes by, more and more data can be added into level 0, which will make a foundation for the model to grow higher. Three mechanisms are defined for the model to grow high, and which are described as follows. The first one is growing step by step so that the data of a specific aspect gradually grows to a higher level (one level at a time). The second one relies on the combination of multiple aspects to generate a new feature at a higher level. The model could leap to grow in the third way where it may grow from the state level directly to the characteristic level. In the following parts of this subsection, some examples are illustrated to show how a model grows to a higher level.

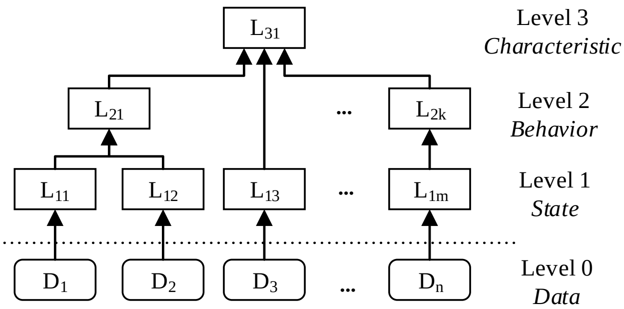

Fig. 6. Growable modeling for becoming higher

As explained in the IM-C and IM-P, we have made a user to choose his/her favorite color, food, sport, music and movie. And previous psychological research has shown that the preferences can reflect a user’s behavior and characteristic. Besides, the increasing data that comes from other sources can also be used to generate a user’s new preference such as we can infer that the user is fond of playing tennis through his twitter data. A combination of the collected information could lead to a better understanding of the user. For instance, if a user have chosen his/her favorite color as red and his/her favorite sport is inferred as tennis through his/her tweets. It will be suggested that the user is action oriented with a deep need for physical fulfillment and he/she might be also full of power and instant judgment, which will cover some features of his/her behavior habit.

Lifestyle can also be inferred from a user’s related GPS locations and movement logs. In our system, the above two kinds of data are set to be analyzed after a certain period. If analysis results for locations show that the user usually goes to different countries. And the results for movement logs show that the user walks more steps than the average standards while sleeps less than the average standards in an irregular manner. It can be inferred that the user travels frequently in his/her work.

C. Growable Modeling for Becoming Closer (GM-C)

Growable Modeling for becoming closer is a process, during which the model is successively adjusted to reduce errors generated in the previous stages, or adapt to the sudden changes in the user’s attributes. The process is shown in Fig. 7, where two kinds of mechanisms for GM-C are illustrated. The first one is *error reduction*. In the phase of model generation, some elements in the model may be inaccurate or have errors due to the lack of information or impression in inference. In order to reduce the errors, more data concerning the specific aspects is needed for gradually approximating to the real value. The second one is *change tracking*. A user's trait could have a sudden change at some situations. Under this circumstance, the change should be recognized and followed by the model. The following are two scenarios in which the above two mechanisms of error reduction and changing tracking are illustrated, respectively.

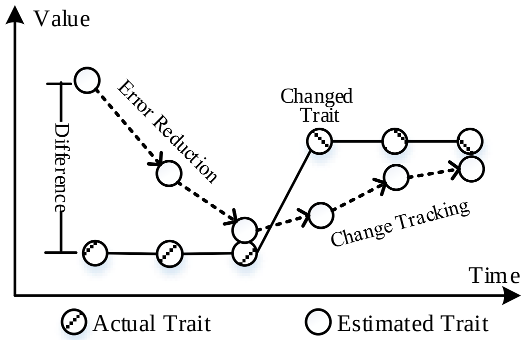

Fig. 7. Growable modeling for becoming closer

A user's initial model is generated during the World Cup and his/her favorite sport is inferred from Twitter. We have found that soccer appears a lot after analyzing his/her recent tweets, and therefore soccer is selected as his/her favorite sport and added into the initial model. However, more tweets or preference choices are collected and found much more information about badminton than soccer. During this period, badminton is possessing more and more priority, and at last badminton replaced soccer as the user's favorite sport.

A user created his/her model as a student. Then the student graduated from university and went to work so that his/her occupation is suddenly altered from a student to an employee while the occupation property in his/her model is still set to be the student. During the growth of the model, his/her related GPS location data, tweets data, etc. is continually analyzed. As the company address always appears in his/her GPS location data and words related to work constantly show up in his/her tweets, the user's occupation is gradually changing from student to employee.

VI. System Prototype and Case Study

The system is mainly consisted of two parts, one is data processing part and the other is modeling part. Besides, there is an interface where a user can choose corresponding functions to process the data, and the proper time to grow and view the grown model stored in the model DB. Our model is designed in a hierarchical structure which can be easily viewed and modified. In order to support this kind of structure, the database is designed using Adjacency list model that contains three columns, i.e. id, parent and name. And the interface is designed using HTML, CSS3 and JavaScript. The system is implemented in Java language, and MySQL database is utilized to store the models.

In a case study, we collected a user's data from a SNS profile, Twitter, preference choices, Web content, app usage records, browser history, movement logs, and GPS-based Location, which are shown in TABLE. III. We processed tweets and analyzed the user's interest, location or even sentiment concerning a specific word. The Web contents were analyzed to know the user's possible occupation and other information. App usage data and browsing history indicated the user's favorite apps and websites, from which we can also infer the user's behaviors. Movement log shows steps of walks/runs and sleep time. Location data contains the user's frequently visited places such as a home or a workplace.

TABLE III. Data and Processing Tools/Programs

Used Data	Processing Tools/Programs
Facebook Profile	Facebook GraphAPI
Twitter Tweet	Twitter4j, AlchemyAPI
Web Content	Google Search API
App Usage	ManicTime, CSV Analyzer
Browser History	ManicTime, CSV Analyzer
Movement Log	CSV Analyzer
GPS Location	Google Now, KML Processor

In the Cyber-I birth stage, the user first registered the system through an email address, then choose favorite color blue, and fill in the Big Five questionnaire. The rough location, Japan, was also generated from the current IP address. By processing these data, an IM-C hierarchical initial structure was generated as shown on the Cyber-I modeling interface in Fig. 8.

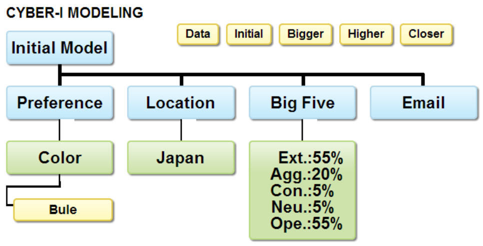

Fig. 8. Modeling interface and an example of IM-C

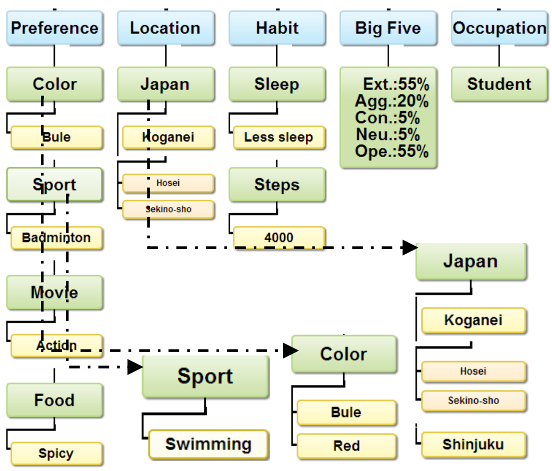

Fig. 9. Examples of GM-B and GM-C

As shown in Fig. 9, the model grows to the five aspects, including preference, location, habit, Big Five and occupation. In the preference part, 3 more aspects (Sport, Movie and Food) are grown from multi-preference choices in IM-P. The location Koganei is grown under the aspect of Japan and finer ones

(Hosei, Sekino-cho) are added along with the coming location data. Sleep and steps aspects are added under habit (generated from Jawbone data) and the aspect student is added under occupation (via Facebook profile). From one week's tweets collected, it was inferred that this user might love swimming and red color. Then, the model controller was in charge of adding swimming and red into their corresponding parent aspect. Moreover, a new finer aspect Shinjuku was added according to the new location data. By analyzing one month's data, it showed that badminton didn't appear but swimming could be found from every week's tweets. Then the badminton aspect is deleted by model controller. Such change means the model grow closer to reduce error.

Three mechanisms for growing higher are shown in Fig. 10. The first one is growing up step by step. The app usage data indicated the four apps (Eclipse, Chrome, Visio and Word) were frequently used. It could infer this user's new features at the higher level, which were some behaviors such as the user may like programing, browsing and often uses office tools to work. After a certain period of time, the third level (characteristic) can also be inferred because the user used these apps every weekday, which means he may live in a regular life. The second one is that the model can directly grow based on Big Five, from which we could infer that the user may appear open and extravert. The third way relies on the combination of multiple aspects to generate new feature at a higher level. The combination of sport and habit showed that he liked playing badminton in weekend, while seemed an unhealthy life in the weekday. Besides, the added location data could suggest the user's locations for studying and playing badminton.

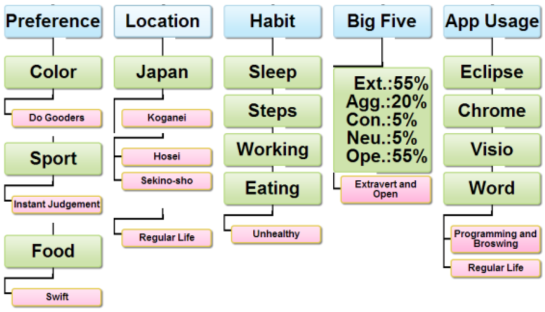

Fig. 10. Exmaples of GM-H

In this case study, an actual user's personal data was collected for one month to establish his own Cyber-I model using our series of modeling approaches. The system prototype and the case study were to implement and verify our growing model mechanisms, which are quite different from traditional user modeling. Our Cyber-I modeling system is not just a simple stereotype for showing user models in an xml file or an ontology description. We try to represent a user's model in a vivid manner and put emphasis on the process of how the model grow. Although our prototype modeling can dynamically show different growth processes from initial model, the modeling is not yet to approximate to the user always as expected due to relatively simple abilities in processing data and trait inference. Besides, the SQL-based database looks not flexible and efficient in handling a hierarchical modeling structure.

VII. Conclusions and Future Work

This research has been focused mainly on growable Cyber-I modeling based on increasing personal data. Various types of personal data were collected from both software tools and sensors for studying the initializations and growths of Cyber-I models. Three basic initial models of IM-C, IM-S and IM-P are generated from the Cyber-I core data, a user's Facebook profile, and preference choices, respectively. We proposed three modeling mechanisms for Cyber-I models to become bigger, higher and closer. A system prototype was built to manage personal data, and models' initializations and growths. A case study was conducted to concretely show how models were initialized and grown.

Though our study has shown the basic ability for Cyber-I models to grow up, much research work still remains. Since there are many types of personal data with quite different formats, size and features, a unified data management scheme must be built. Also, a database containing a set of data processors to handle various data is necessary. Further, the model controller has to be improved to automatically decide which of the three growths will be made with analyzing the processed data. Along with data comes, an important issue is to determine what conditions a model can grow. A friendlier GUI will be made for users to effectively interact and manage the personal data and their models. Surely, more case studies and many experiments should be conducted to evaluate the system for further improvements.

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