Are You Satisfied with Your Recommendation Service?: Discovering Social Networks for Personalized Mobile Services

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Abstract. Most of recommendation mechanisms have been attempting to identify a set of cohesive user groups (or clusters) of which members in the same group might be interested in a common area (e.g., movies and musics) than others. Practically, this assumption is not working well, because the statistical analysis to extract simple demographic features (e.g., ages, genders, and so on) can not find out personal context in a certain situation, i.e., a more specific recommendation for each person. In order to solve this problem, we want to take into account social relations (particularly, kin relations) to identify each person. As aggregating the social networks, we can build a social network for making various social relations extractable. Most importantly, we are introducing our experiences on discovering social networks for providing personalized mobile services. Real customer information has been provided from KT Freetel (KTF), one of the major telecommunication companies in Korea. This work is an on-going research project for delivering personalized information to mobile devices via the social networks.

1 Introduction

To efficiently support personalized service, various types of information can be applied for modeling a target user's preference. One of well-known approaches, the so-called collaborative filtering [1,2], is to compare profiles of people. Such profiles are composed of ages, genders, occupation, and so on. Main assumption of this approach is that the more closer profile should be the more like-minded people. It means that two persons whose age are same are more probably interested in the same movie, rather than people who are older (or younger).

However, in real world, current personalized services have not shown efficient performance, people are not satisfied with the services at all. We think that most of the personalization mechanisms are simply trying to find out hierarchical clustering structure (this is very similar to the decision tree) identifying cohesive user groups of which members in the same group might be interested in a common area (e.g., movies and musics) than others [3]. This statistical analysis to extract simple demographic features by comparing user profiles [4] (e.g., ages, genders, and so on) can not find out personal

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context, i.e., what they are looking for in a certain situation. In other words, the personal recommendation for each user is supposed to be more specific.

In order to solve this problem, we mainly take into account two more conditions. Firstly, social affinity is regarded as a reasonable evidence to predict the personal context. For example, social relations (particularly, kin relations and friendships) can be assumed to identify each person's context more specifically. When he is looking for his father's birthday present, it is much more probable that he is looking for what his father wants than what he does. As aggregating the social networks, we can build a social network for making various social relations extractable. This social network can play a role of integrating multiple contexts which are inter-related between each other (e.g., parents and children).

Second condition is location, i.e., geographical position where you are. The personal context basically changes over time. In order to support better personalization, the service should be timely activated. For example, a user who is in a department store is expected to buy a certain product, rather than to go to restaurant.

More importantly, these two types of conditions can be merged for better personalized recommendation. Given two person who are i) linked (highly related) on a social network and ii) located in (or moving to) a close place, we can recommend very reasonable information to them. Especially, in this research project, we have been focusing on the mobile users joining KTF (KT Freetel) services. The problem is that the social networks are hidden. Thereby, we want to discover the hidden social network from usage patterns of mobile devices.

The outline of this paper is as follows. In the following Sect. 2, we will describe the problem on mobile communication. Sect. 3 and Sect. 4 show our heuristic approach to discover social networks among mobile users, and the whole system architecture, respectively. Sect. 5 will mention some of related work on personalization and building social network between mobile users. Also, we want to discuss some important issues. In Sect. 6, we draw a conclusion of this paper, and address the on-going and future work of this project.

2 Problem Description

To establish better personalization, we want to discover a social network from a given dataset. Generally, a social network is a graph-structured information.

Definition 1 (Social network). *A social network $\mathcal{S}$ is defined as*

$$\mathcal{S} = \langle \mathcal{N}, \mathcal{A} \rangle \tag{1}$$

where $\mathcal{N}$ and $\mathcal{A}$ are a set of participants $\{n_1, \ldots, n_{|\mathcal{S}|}\}$ and a set of relations between the participants, respectively.

In particular, $\mathcal{A}$ is simply represented as an adjacency matrix where

$$\mathcal{A}_{ij} = \begin{cases} 1 \text{ if } n_i \text{ links to } n_j; \\ 0 \text{ otherwise,} \end{cases}$$

and it is not necessarily symmetric, because we want to consider the directionality of the relations. For instance, the matrix is shown, as follows.

$$\mathcal{A} = \begin{array}{c} \\ n_1 \\ n_2 \\ \dots \\ n_{|\mathcal{S}|} \end{array} \begin{array}{c} \begin{array}{cccc} n_1 & n_2 & \dots & n_{|\mathcal{S}|} \end{array} \\ \begin{pmatrix} 0 & 1 & \dots & 0 \\ 1 & 0 & \dots & 1 \\ \dots & \dots & \dots & \dots \\ 1 & 0 & \dots & 0 \end{pmatrix} \end{array} \tag{2}$$

More importantly, in this work, the social network can contain multiple context together.

Definition 2 (Multiplex social network). *A multiplex social network $\mathcal{S}^+$ is defined as*

$$\mathcal{S}^+ = \langle \mathcal{N}, \mathcal{A}, \mathcal{C} \rangle \tag{3}$$

where $\mathcal{N}$ and $\mathcal{A}$ are the same components as normal social networks $\mathcal{S}$. Additional component $\mathcal{C}$ is a specified social relation attached to $\mathcal{A}$.

A simple example of multiplex social networks is shown in Fig. 1. Links in this social network are attached with six different contexts (e.g., *isSisterOf*, *isMotherOf*, and so on).

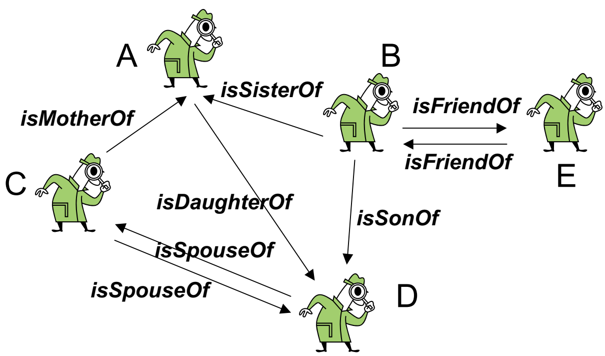

Fig. 1. A multiplex social network

Now, we want to explain about the datasets sampled from KTF legacy databases where raw records are stored. Mainly, it consists of three parts; i) registration profiles, ii) device (and service) specifications and iii) their calling patterns of over 60 thousand subscribers (mobile users). A set of fields of registration profiles are composed of

1. Name (first name and last name)
2. Social security number (partially encrypted)
   – Date of birth
   – Gender
   – Place of birth
3. Address
4. Job, Hobby, etc. (not provided).

As second part, the information about the devices and services are

1. Phone number
2. Device model
   – Communication protocol types (e.g., 2G, 3G)
   – Bell, sound, color, CDMA, GPS, KBANK types
3. Payment
   – Payment method (e.g., bank transfer, credit card, etc.)
   – Delegated person (e.g., name and social security number)
   – Payment creditability (e.g., history, postpone)

Third kind of information is indicating usage pattern of calling and SMS.

1. Calling
   – Calling number
   – Time of calling
   – Duration of calling
2. SMS
   – Receiver number
   – Time of Texting
   – Types of Texting (e.g., SMS and MMS)
3. Data communication types
   – Service types (e.g., CDMA/WCDMA, BREW/WIPI/VOD, DPP, RTSP, etc.)
   – Status of Charge (e.g., Start, Stop, Interim-Update, PPP Session Stop, and Accounting-On/-Off)
   – Amount of sent/received packets
4. Location
   – Scheme (e.g., GPS, CELL, and GPS+CELL)
   – Map viewer and map image formats (e.g., BMP, SIS, GML, and CGML)
   – Location information (e.g., X, Y, Z coordinations, etc.)

3 Heuristic Approach

These datasets are applied to predict social relations between mobile users by our heuristics. We have been tried to formalize the scenarios which are easily understandable to people in a common sense. Thus, each scenario can be matched to a set of social relations. Given a certain social relation, we have investigated as many cases as possible. To do so, we have built a decision tree by two ways of;

– interviewing with experts in KTF, and
– machine learning software packages (e.g., clementine and weka).

For example, in case of family relations such as *isFatherOf* and *isFamilyWith*, which are the most important social relation in this project, we can say that n_A is a father of n_B when;

– $(Payment(n_B) = n_A) \wedge (Age(n_A) - Age(n_B) \in [30, 50]) \wedge (Lastname(n_B) = Lastname(n_A))$

- $(Location(n_A, AtNight) = Location(n_B, AtNight)) \wedge (Age(n_A) - Age(n_B) \in [30, 50]) \wedge (Lastname(n_B) = Lastname(n_A))$

In addition, this logical expressions can be dynamically updated over time. More importantly, the social relations are semantically represented as concept hierarchy. For example, *isFatherOf* and *isBrotherOf* are subclasses of *isFamilyWith*. Thus, when the given information is not clear or enough, we can replace it to one of its superclass relations. (In fact, this issue is planned to work in near future.)

4 System Architecture

Our system is called NICE, which stands for New-generation Intelligent Content dElivery. The whole of system architecture is shown in Fig. 2.

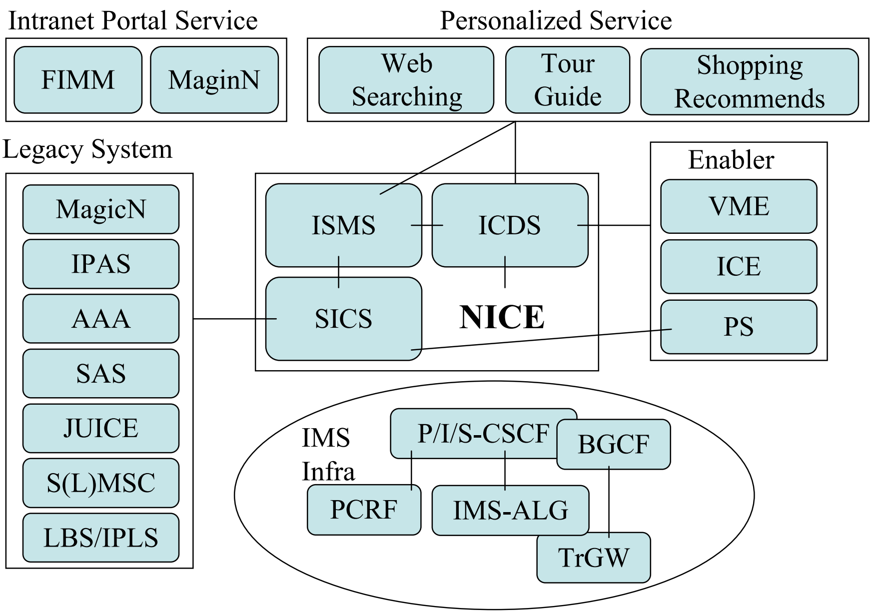

Fig. 2. System architecture of NICE

Our system is mainly divided into four parts. Legacy system is basically playing a role of data storage, as follows.

- IPAS - Internet Protocol Accounting Server
- AAA - Authorization, Authentication, Accounting
- SAS - Subscriber Analysis System
- JUICE - Storage database server for all subscriber's profiles
- S(L)MSC - Short (Long) Messaging Service Center
- LBS/IPLS - Location Based Server/Internet Protocol Location Server

As second component, IMS (IP Multimedia Subsystem) infrastructure can collect calling patterns from WCDMA, and be aware of charging status. The modules are shown, as follows.

– (P/I/S) CSCF - Call Session Control Function
– BGCF - Breakout Gateway Control Function
– PCRF - Policy & Charging Rule Function
– IMS & ALG - IP Multimedia Subsystem & Application Layer Gateway
– TrGW

These modules are related to fulfilling personalized service dynamically.

Third part is enabler for controlling the data streams.

– VME - Video Media control Enabler
– ICE - IMS Community Enabler
– PS - Presence Server

Finally, four part is main components of NICE system.

– ISMS (Intelligent Subscriber Management Server) can manage and support intelligent subscriber information cleansing (generation, storage and update), personalized social network builder, and subscriber status/location information.
– ICDS (Intelligent Content Deliver Server) can manage and support subscriber's log-on/-off, dynamic user interface, user sessions, SIP/HTTP/MSRP/RT(C)P protocol, personalized pop-up, intelligent web searching, and personalized web content.
– SICS (Subscriber Information Collection Server) can conduct subscriber's information collection/summarization/scheduling, subscriber information storage, and subscriber information transferring.

5 Related Work and Discussion

Most similarly, there have been two works. In [5], they have proposed a way of measuring the closeness between two persons to build a social network. Mainly they are focusing on the calling patterns, when (and how frequent) people are calling.

Also, in [6], their project "reality mining" has introduced experimental results for evaluating several hypothesis. These hypothesis has been compared to self-reports provided by the human users.

Personalization based on multi-agent systems has been introduced in MAPIS [7]. With regards to the business-oriented work, in [8], personalization process on e-commerce has been conducted by three modules; i) marketing strategies, ii) promotion patterns model, and iii) personalized promotion products. Especially, location-based personalization services has been implemented, e.g., NAMA [9].

6 Concluding Remarks and Future Work

This work is an on-going research project for building social network between mobile users. In this paper, we have described our research project for delivering personalized content to mobile users. In order to do so, we have introduced our heuristic approach to construct meaningful social networks between mobile users. Each context included in a social network has been combined with spatial context to better recommendation.

Future work, we are planning to put the calling patterns into the social network which has been built by expert's heuristics. It will make the social network more robust, and dynamically evolvable. Evaluation method has been also considered to verify whether the personalized service is reasonable or not. Finally, as proposed in [10], we have to implement a visualization functionality for better understandability.

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