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An Adaptive Match-Making System reflecting the explicit and implicit preferences of users

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ABSTRACT

This is a study of a matchmaking system that adaptively adjusts the recommendation model reflecting the user's implicit preference as well as the explicit one. Many matchmaking systems require their users to assign the level of importance, referred to as weight, of a certain attribute such as age, job, and salary when they select dating partners. However, many users do not know the exact level of importance of each attribute and thus, feel burdened to assign weights. Also, even though users explicitly assign weights, they are often in contrast to the users' actual behaviors in many cases. This paper suggests a new match-making system called Adaptive Match-Making System (AMMS) that automatically adjusts the weight of each attribute by analyzing the user's previous behaviors. AMMS provides recommendations for newly entered users on the basis of their explicit-weights assigned by users. However, as the user's behavioral records are accumulated, it begins to build the logistic regression model in order to find out the user's implicit weights and reflects them in proportion to the accuracy of the resulting model. The prototype of AMMS is implemented by using Java and the web editor. It is applied to the created artificial dataset based on the real survey results from major matchmaking companies in Korea.

1. Introduction

A matchmaking system is a type of recommender systems that provides a set of dating partners suitable for the user. In order to recommend the right dating partners, many matchmaking systems collect profile attributes such as age, job, education of users, ideal attributes of the mate, and weights of these attributes. Through this collection, the users present how much they consider each attribute important when selecting dating partners. For example, one of the major online dating sites, Match.com, requires their users to answer how much he/she considers certain attributes of dating partners important such as ethnicity, eye color, educational level, and job category on a scale from 0 to 10. The more important the attribute, the higher the weight assigned by the user.

However, on the user's side of view, it is difficult and troublesome to assign weight for each attribute by himself/herself because many users may not recognize the exact level of importance they feel for each attribute. Also, in some cases, the weights which the user recognizes by intellect may be different from the implicit weights which he/she intrinsically feels. Moreover, even though the user knows the exact level of weights for each attribute, these can be modified by the environment. Regan (1998) argued that the selection criteria for finding the ideal mate are not set in stone, and people can and do modify their standards as a function of various selection pressures such as time (Regan, 1998). Specifically, people compromise their criterions of ideal partners from time to time.

This paper suggests a new matchmaking system called Adaptive Match-Making (AMMS) that automatically adjusts the weight of each attribute by analyzing the user's previous behaviors. The main idea of AMMS is to adaptively adjust the weights reflecting the user's implicit and explicit preferences. First, AMMS collects the user's profile information such as age, education, job, height, and income and also gathers the ideal partner's values for the same attributes. Then, it produces preference scores of the user to a certain partner. In this process, AMMS uses the weighted distances by calculating the distance between the attribute values of the user's ideal mate and the potential partner's real values. The weights are initially set by the user manually on the basis of his/her explicit preference. However, if the user's behavioral records have been accumulated and have reached a certain level, AMMS begins to analyze the user's implicit preference by learning the data and thus, produces the implicit weights. More specifically, AMMS builds a logistic regression model for the user having more number of previous message sent records than the criterion and produces the implicit weights using the coefficients of the model. Next, the produced implicit weights are applied to the matchmaking system in proportion to the model's accuracy performance, so that the more accurate the model is, the more the implicit weight reflected to the model. The preference score of a potential partner to the user is also calculated in this way and the mutual preference score

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is calculated considering the reciprocity between the user and the partner. Finally, AMMS recommends the partners to user having highest mutual preferences scores.

AMMS regularly updates the recommender model for the user as the quantity of his/her behavioral records increase. Thus, the user can be provided with newly created recommendation lists reflecting his/her recent implicit preference. Also, AMMS does not have a cold start problem since recommendation at the early stage is performed based on users' explicit preferences. The prototype of the AMMS is implemented by JAVA and the NAMO web editor.

The rest of this paper is organized into five sections. Section 2 presents the research related to the current study. Section 3 suggests the architecture of Adaptive Match-making System (AMMS) and Section 4 shows the prototype of the AMMS. Finally, in Section 5, concluding remarks are described.

2. Related research

Previous researches on matchmaking systems have commenced relatively in the recent years, and only a limited number of papers are published in this area. The early researches of matchmaking systems apply conventional recommendation techniques to the domain of online dating. Brožovsk and Petricek (2007) applied conventional recommenders such as collaborative filtering methods and global algorithms to the matchmaking area and compared their performances quantitatively (Brožovsk & Petricek, 2007). This research indicated that online dating recommenders have a different characteristic from conventional product recommenders, such as reciprocity between matched partners. Thus, these recommenders should be treated differently (Mori, Kajikawa, Kashima, & Sakata, 2012). However, they did not focus on solving this issue in this paper. Krzywicki, Wobcke, and Cai (2010) proposed several recommenders designed for online dating based on collaborative filtering methods (Krzywicki et al., 2010). In this research, they insisted that collaborative filtering based on positive interactions of users, without using profile information, can be a viable approach for online dating recommenders.

However, collaborative filtering methods do not utilize profile information of users and their ideal partners, such as age, education, and income, which are significantly considered in online dating. Thus, some other researches have proposed to use content-based methods for online dating recommenders, so that profile information can be actively used for the matchmaking process. Hitsch, Horta_csu, and Ariely (2010) studied as to which personal characteristics are more important for certain groups of users (Hitsch et al., 2010). They investigated mate preferences, match formation, and the resulting attribute correlation and sorting patterns in terms of profile information using a data set from an online dating site. Fiore and Donath (2005) also observed a positive correlation in the personal attributes of people who match well (Fiore & Donath, 2005).

The profile information used as an input of content-based methods is often collected from users by asking their customer to answer the closed-formed questionnaire. However, users are generally reluctant and feel burdened to provide highly private information such as preferences of mates and attribute significance (Kelly & Teevan, 2003; Nichols, 1997; Oard & Kim, 1998). Moreover, although they provide such information to matchmaking systems, the information is often contrary to their actual behaviors (Pizzato, Chung, Rej, Koprinska, & Yacef, et al. 2010; Pizzato, Rej, Chung, Koprinska, & Kay, 2010).

In order to overcome this limitation, some matchmaking systems find out users' implicit preferences by analyzing their behavioral records instead of directly asking the users. Pizzato, Chung et al. (2010) and Pizzato, Rej et al. (2010) suggested a new method to find out users' implicit preferences by learning from their past contact history on the online dating site (Pizzato, Chung, et al. (2010); Pizzato, Rej, et al. (2010)). This research proposed to use the explicit information about users' self profile while utilizing the implicit information about the users' preferences for matchmakings. In their other research, they also addressed the issue of reciprocity of matched partners, which is related to our research, and suggested a matching system called RECON in order to solve this problem.

By learning users' implicit preferences, it becomes convenient for the user. However, this approach can only be applied for users having a large number of behavioral records. Specifically, it is hard to analyze the implicit preference of newly entered users or passive users having only a small number of historical records. This problem is referred to as the cold start (Schein, Popescul, Ungar, & Pennock, 2002). Many previous researches have been conducted in order to solve this problem (Kim, Alkhaldi, & El Saddik, 2011; Park & Tuzhilin, 2008; Truong, Ishikawa, & Honiden, 2007; Ungar & Foster, 1998). One of the widely used solutions is the aforementioned content-based method. In this article, we initially used content-based methods by utilizing the users' explicit preferences in order to avoid the cold start problem. However, when the historical data became large enough to be analyzed, we started to use the users' implicit preferences as well.

3. Adaptive Match-Making System

In this section, we suggest a new matchmaking system called Adaptive Match-Making System (AMMS) that recommends dating partners based on the user's implicit preferences as well as his/her explicit ones. The main idea of AMMS is recommending dating partners based on users' explicit preferences at the initial stage; however, implicit preferences are reflected as well, as the behavioral data are accumulated at a certain level. In Section 3.1, the common research settings used throughout this paper is introduced. Next, in Section 3.2, the overall matchmaking process of AMMS for recommending desirable dating partners is introduced. Finally, Section 3.3 describes the method to analyze users' implicit preferences by using their behavioral data and to decide how much of these implicit preferences should be reflected for recommending dating partners.

3.1. Research settings

The suggested Adaptive Match-Making System (AMMS) initially gathers user's attribute values about his/her own profile, those of preferable dating partners, and the weights of each attribute. User data C consists of his/her profile attributes p such as age, job, education, salary, and height, and those of his/her preferable dating partner's attributes e for the same attributes. Also, it has weight attributes w, which represents how much C considers each attribute important when selecting dating partners. Then, the set of user m_i can be presented as:

$$
\begin{aligned}
C(m_i) = \{ & p_{\text{age}}(m_i), p_{\text{job}}(m_i), p_{\text{education}}(m_i), p_{\text{salary}}(m_i), p_{\text{height}}(m_i), \\
& \times e_{\text{age}}(m_i), e_{\text{job}}(m_i), e_{\text{education}}(m_i), e_{\text{salary}}(m_i), e_{\text{height}}(m_i), \\
& \times w_{\text{age}}(m_i), w_{\text{job}}(m_i), w_{\text{education}}(m_i), w_{\text{salary}}(m_i), w_{\text{height}}(m_i)\}
\end{aligned}
$$

Additionally, C has behavioral data r which shows whether C has sent messages to the recommended partners or not. For example, a set of message sent record $R_{m_i \to f_j} = \{r_{m_i \to f_j}\}$ presents whether user m_i sent messages to the other user f_j or not. If m_i sent messages to e f_j, then $r_{m_i \to f_j}$ is set to "Y"; however, if m_i has not sent messages to f_j after being recommended to f_j, then $r_{m_i \to f_j}$ is set to "N". If f_i has not been recommended to m_i previously, then $r_{m_i \to f_j}$ stays a *null* value. Thus, if there are 10 numbers of female users from f_1 to f_{10}, and