# Target Advertisement Service Using TV Viewers' Profile Inference

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**Abstract.** Due to the limitation of broadcasting service, in general, TV programs with commercial advertisements are scheduled to be broadcasted by demographics. The uniformly provided commercial can not draw many TV viewers' interest, which is not correspondent to the goal of the commercial. In order to solve the problem, a novel target advertisement technique is proposed in this paper. The target advertisement is a personalized advertisement according to TV viewers' profile such as their age, gender, occupation, etc. However, viewers are usually reluctant to inform their profile to the TV program provider or the advertisement company because their information can be used on some bad purpose by unknown people. Our target advertisement technique estimates a viewer's profile using Normalized Distance Sum and Inner product method. In the experiment, our method is evaluated for estimating the TV viewers' profile using TV usage history provided by AC Neilson Korea.

## 1 Introduction

Streaming service on the net such as internet broadcasting or web-casting [1] has been commonly used since a few years before, IPTV service [2] is also expected to be launched on the broadband network. Due to the invention and development of web-casting, the concept of the traditional broadcasting service is being refined. The traditional broadcasting service usually provides contents to unspecified individuals regardless of users' interests of the contents. For example, commercial advertisements are scheduled to be broadcasted by the demographic information such as TV program rating, age and gender group, and TV viewing time band. Unlike TV programs, the advertisements along with the programs are not selected by TV viewers' preference due to the limitation of the TV broadcasting environment. The randomly provided commercial can not draw many TV viewers' interest, which is not correspondent to the purpose of commercial advertisements: "providing advertisements to the right people in the right time." However, web-casting can allow users and content providers or servers to interact with one another by means of the bi-directional channels [3],

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which is the critical factor for providing personalized advertisement service. The personalized advertisement service targets the right commercials to the right users interested in them, and it is called target advertisement (TAD) in this paper.

To our best knowledge, not many researchers [4-6] have studied for developing target advertisement services. They usually cluster users and make groups according to similarity of their profiles and for a new-comer, find a group whose representative profile is close to the profile of the new-comer, to whom then the preferred advertisements of the group are provided to the new-comer. The clustering is done by collaborative filtering technique [7] based on users' profile. In their methods, TV viewers' profile such as gender, age, and occupation are explicitly informed to the TV content providers by personally inserting their information into the set-top box or the computer connected to the digital TV set. In general, people are reluctant to register their profile to the servers because of its improper use by unknown persons.

In order to serve TAD along with protecting users' privacy, we need to infer users' profile by analyzing users' implicit content consumption behaviors. In this paper, we introduce a novel method for inferring the users' profile with TV viewers' content consumption history such as TV watching day, time, and the preferred TV program genre. According to the target profiles for the inference, two different inference techniques are developed. One is for inferring a new viewer's age using a collaborative filtering technique. The technique groups TV viewers according to their ages, for a new viewer, find the age group whose preferred TV genre is similar to that of the new viewer's TV genre preference, and then provides the preferred commercial advertisements of the age group to the new viewer. The other is for inferring a new viewer's age and gender together using the look-up table method. In general, the more detail inference needs more TV viewers to increase the coverage of the cases of the inference. That is the reason why we use the look-up table for inferring age and gender together not using the collaborative filtering used in the age inference. Also, we design and model the prototype of our target advertisement system based on the inferred profile using the algorithms.

The remainder of this paper is organized as follows. Section 2 demonstrates the overall architecture of the target advertisement service. Section 3 describes our algorithms for inferring a viewer's profile. In Section 4, we show the experimental result of our algorithms using 2,000 TV viewers' TV program watching history and design and implement the prototype of the target advertisement service. We conclude our paper and propose future research work.

## 2 Overall Architecture of Target Advertisement Service

Fig. 1 illustrates the expected overall architecture of the target advertisement service in the condition that the interactive communication between content providers and TV viewers is possible by a web-casting scheme. There are three major users of the system such as content providers, advertisement companies, and TV viewers in the system. The content providers provide broadcasting contents with commercial advertisements to the TV or VOD (Video on Demand) viewers. The advertisement companies provide commercial items to the content providers. The target advertisement service system consists of three agents such as profiling agent (PA), interface agent

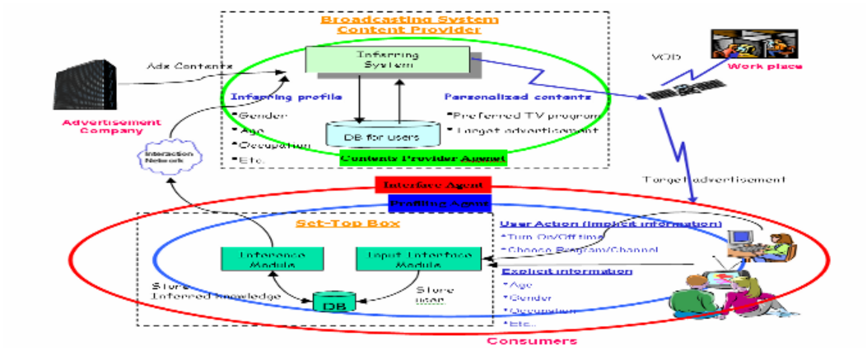



**Fig. 1.** The architecture of target advertisement service

(IA), and contents provider agent (CPA). The PA gathers the explicit information, e.g., TV viewers' profiles, directly input by TV viewers and the implicit information, e.g., content consumption behaviors such as TV program, viewing day, viewing time, and etc. The information is sent to the IA which is the graphic user interface (GUI) capable of the interaction between the PA and the CPA. The IA can be a set-top box connected to a TV set in viewers' house. The IA stores the received information into database through the input interface module. At the inference module in the IA, the stored viewer's consumption behavior data is analyzed for inferring his/her preferred TV genres and viewing day and time using any user's preference inference. The inferred knowledge (preferred TV genre in this paper) and the directly input profiles are sent to the CPA through the interactive network and stored into the database of viewers. Here, we assume that a restricted number of viewers sent their profiles to the CPA, e.g., around 10,000. The CPA analyzes the stored data and clusters the viewers according to the similarity of their profiles and the inferred information. For the viewers who are reluctant to send their profiles to the CPA, his/her profile can be inferred in the inference module using our proposed method which is explained in the next section. If an advertisement company requests the CPA to broadcast the commercial advertisements, the CPA provides the targeted viewers the commercial advertisements along with their preferred TV programs via the interactive networks.

In the following section, we describe our TV viewer profile inference method using the implicit information such as TV usage history.

## 3 TV Viewer Profile Inference

### 3.1 Age Inference System Using Normalized Distance Sum (NDS)

In general, the similarity of TV viewers' preferred genres can be characterized according to their age or gender. For instance, the documentary programs are usually popular favor for 30s and 40s man, while the show programs are for 10s and 20s. For each age group, the statistical preference of each genre can be calculated using Equation (1).

$$p_{i,k,a} = g_{i,k,a} / \sum_{i=1}^{I} g_{i,k,a} \tag{1}$$

where $g_{i,k,a}$ is the frequency of watching genre $i$ of a TV viewer $k$ in his/her age group $a$ during a predetermined period. Also, $I$ is the total number of the genres. From the calculated values of the probabilities, the genres can be ordered from the highest ranked genre having the largest probability to the lowest ranked genre having the smallest probability. The ordered genres can be expressed with the vector form such as

$$V_{k,a} = \{R_{1,k,a}\ R_{2,k,a}, \cdots, R_{j,k,a}, \cdots, R_{I,k,a}\} \tag{2}$$

where $R_{j,k,a}$ and $V_{k,a}$ is the $j^{th}$ ordered genre and the vector of the ordered genres of a TV viewer $k$ in his/her age group $a$, respectively. For each viewer in group $a$ in the database, the order of the preference of the genres can be various. If there are $K$ number of viewers in the database in the content provider, the representative genre at $R_{j,k,a}$ can be decided by the frequencies of the consumption of the genres at the $j^{th}$ rank for viewer $k = 1$ to $k = K$. At rank $j$, the genre having the largest frequency is considered as the representative genre, denoted as $\tilde{R}_{j,k,a}$. Also, the representative vector, denoted as $\tilde{V}_a$, for ages $a$ can be denoted as

$$\tilde{V}_a = \{\tilde{R}_{1,k,a}\ \tilde{R}_{2,k,a}, \cdots, \tilde{R}_{j,k,a}, \cdots, \tilde{R}_{I,k,a}\} \tag{3}$$

For a new (or test) TV viewer $t$, who has not been experienced by the content provider or has not input the viewer's profile to the interface agent, the vector of the order of the viewer's genre preference, denoted as $V_t$, can be obtained from his/her TV genre consumption behavior collected during a predetermined period and denoted as follows:

$$V_t = \{R_{1,t}\ R_{2,t}, \cdots, R_{j,t}, \cdots, R_{I,t}\} \tag{4}$$

The measurement of the similarity of the new viewer and each age group can be obtained using NDS (Normalized Distance Sum) [8], one of image retrieval methods, and Vector correlation, measuring the similarity between two vectors. The NDS method provides the weights to the mismatch of order of genres according to the rank of the genres for measuring the similarity between two vectors $\tilde{V}_a$ and $V_t$. For example, if drama is the first ranked genre of a new viewer, the 3rd ranked for 20s, and the 2nd ranked for the 30s, then the degree of the mismatch of rank of drama between the new viewer and 20s and the new viewer and 30s. The degree of the mismatch for the ranks is called unsuitable distance in [8]. The unsuitable distances for all ranks can be normalized, which is used for the measurement of the similarity between vector $\tilde{V}_a$ and vector $V_t$ as shown in Equation (5).

$$NDS(\tilde{V}_a, V_t) = \sum_j \{I - j + 1 \mid j : mismatchedrank)\} / I(I+1)/2 \tag{5}$$

For example, Table 1 shows an example of vector $\tilde{V}_a$ and vector $V_t$ and the total number of genre, I, is 46. The mismatched genres of $V_t$ are sports and comics to those of $\tilde{V}_a$ along with ranks 3 and 46. In Equation (5), the index j means the mismatched rank j in $\tilde{V}_a$. As the equation in the numerator of Equation (5), for the mismatched rank 3, the unsuitable distance is 44 (46-3+1=44) and for the mismatched rank 46, the unsuitable distance is 1 (46-46+1). From the numerical results, the penalty of the mismatch of higher ranked genre is given more than that of lower ranked genre. For all age groups, the NDSs of the new viewer can be computed using Equation (5), and the age band of the new viewer can be estimated the age band of the age group having the smallest value of NDS as denoted in Equation (6).

$$A\hat{g}es(t) = \min\{NDS(\tilde{V}_a, V_t \mid a \in A)\} \tag{6}$$

where $A\hat{g}es(t)$ is the estimated age band of new viewer or test viewer $t$. By the estimated age band, the TV content provider can provide the commercials suitable for the age band. For example, if the new viewer's age band is estimated 10s, the advertisements related to electronic goods such as MP3, DVD, etc. can be provided. Fig. 2 is the schematic diagram for the NDS method, where G represents the age group such G1 (age 0~9), G2 (age 10~19), …., G7 (age over 60).

**Table 1.** An example of $\tilde{V}_a$ and $V_t$

| Rank | 1 | 2 | 3 | ....... | 45 | 46 |
|---|---|---|---|---|---|---|
| $\tilde{V}_a$ | Drama | News | Sports | ....... | Documentary | Comics |
| $V_t$ | Drama | News | Comics | ....... | Documentary | Sports |

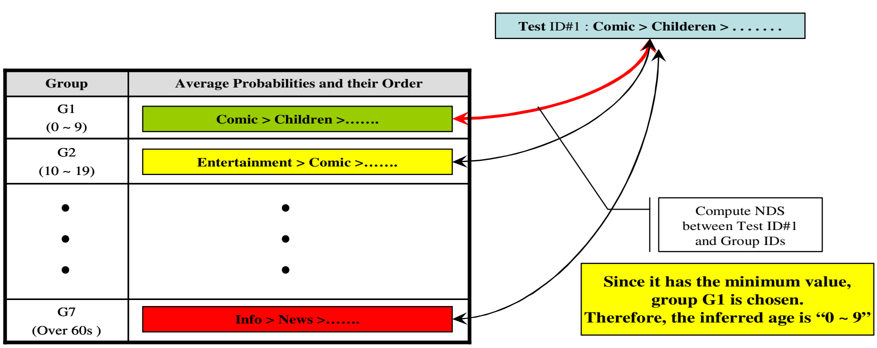



**Fig. 2.** The TV viewer's age inference using the NDS method

### 3.2 Age and Gender Inference System Using Vector Correlation

At the previous section, we demonstrated how to estimate a new viewer's age band using NDS technique. Sometime, more information about viewers' profile can increase the efficiency of the target advertisements. If the content providers know viewers' age and gender both, more detail commercial advertisement can be possible than they know viewers' age band. For example, if a viewer's age and gender are estimated 20 and woman, the content providers provide the advertisement of beauty goods such as cosmetics, accessories, etc.

As mentioned in the introduction section in this paper, in general, the more detail profile inference needs more TV viewers' consumption history which can increase the coverage of the cases of the inference. In order to take into the consideration for inferring a viewer's age and gender, we build the look-up table (LUT) of the order of the statistical preferences of genres for the viewers (reference viewers) in the database of the content providers as shown in Fig 3, where the value in the parenthesis next to the genres indicates their statistical preference.

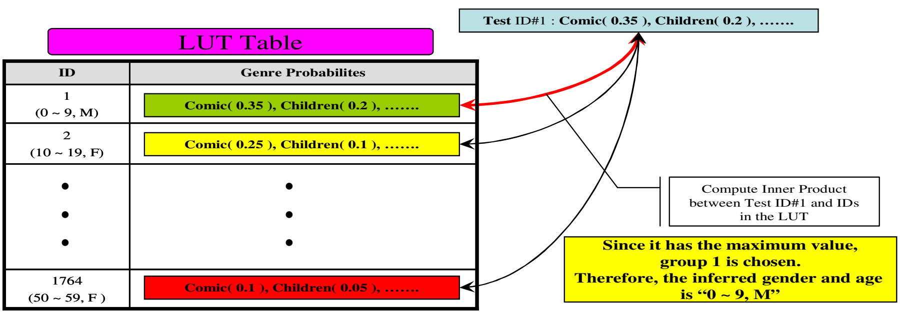



**Fig. 3.** Age and gender inference using LUT

When a new viewer comes, we can find the viewer in the reference viewers whose consumption behavior is very similar to that of the new viewer. The similarity between the vectors of the statistical preferences of the new viewer and each reference viewer can be calculated by the inner product between the vectors as shown in Equation (7).

$$Inn(V_{r_j}, V_t) = \cos\theta = V_{r_j} \cdot V_t / \|V_{r_j}\| \cdot \|V_t\| \tag{7}$$

where $Inn(V_{r_j}, V_t)$ the inner product of $V_{r_j}$ and $V_t$, which is the vector of the genre preference of $j^{th}$ reference viewer and the new viewer $t$, respectively. For all reference viewers, the inner product of the new viewer and each reference viewer can be computed using Equation (7), and the new viewer's age and gender can be estimated as the reference viewer's age and gender who having the maximum inner product as denoted in Equation (8).

$$\hat{ga} = \max\{Inn(V_{r_j}, V_t) \mid j \in J\} \tag{8}$$

where $J$ is the total number of reference viewers in the LUT. Fig 3 describes the schematic scheme of the vector inner product method of the reference viewers and the new viewer from the LUT.

# 4 Experimental Results and System Implementation

In this chapter, we show the accuracy of the proposed two profile inference methods using 2522 TV viewers' (Men: 1243, Women: 1279) usage history collected from Dec., 2002 to May, 2003. The NDS method is applied for inferring a viewer's age band when the content providers know the reference viewers' gender and the inner product method using the LUT is for a viewer's age and gender together when the content providers do not know the reference viewers' age and gender together. At the later section in this chapter, we show the implementation of the prototype of the target advertisement service system enabling target-oriented advertisement service based on our inference methods.

## 4.1 Accuracy of Our Profile Inference Methods

For the age band inference, we divided the TV usage history data into two groups; one is training data and the other is test data. The training data was randomly selected at 70% (1764) from the total data and the test data at 30% (758). Training data was classified into 7 age groups such 0~9, 10~19, . . , over 60. Table 2 shows the accuracy for the test data when our age band inference using the NDS method for the case that only the gender information is known.

Table 3 shows the accuracy of NDS method and Inner product method using the LUT for the case that the age and gender information are not known. The accuracy for the age inference method is about 77%. The accuracy of the ages for 30s and 40s is relatively high. From the result, we can infer that the range of their TV genre preference can not be wide, compared to the other age groups. In the mean while, the accuracy of the age of 20s is about 53%, which indicates that their TV genre preference can be wide.

Using NDS method, we can infer viewers' gender with the same way of inferring the age band. From Table 3, the Inner product method outperforms the NDS method when the reference viewers' age and gender are not known because the data sparseness happens when the NDS method is used for inferring more detail profile, as mentioned in the previous section. As seen in Table 3, we obtained 30.38% accuracy with NDS method and 39.42% accuracy for the men in 50s. With the Inner product method, we obtained average 67.4% accuracy and 89.37% accuracy for the women in 50s.

**Table 2.** The accuracy of the age band inference using the NDS method

| Age Group | Accuracy (%) |
|---|---|
| 0 ~ 9 | 66.90 |
| 10 ~ 19 | 77.60 |
| 20 ~ 29 | 53.53 |
| 30 ~ 39 | 89.05 |
| 40 ~ 49 | 89.08 |
| 50 ~ 59 | 77.34 |
| 60 ~ | 75.20 |
| Total | **77.01** |

**Table 3.** The accuracy of the age and gender using the Inner product method and NDS

| Gender & Age Group | Accuracy (%) | |
|---|---|---|
| | NDS | Vector Correlation |
| 0 ~ 9, M | 37.81 | 62.14 |
| 0 ~ 9, F | 36.11 | 84.15 |
| 10 ~ 19, M | 31.73 | 55.53 |
| 10 ~ 19, F | 34.44 | 79.57 |
| 20 ~ 29, M | 30.36 | 58.01 |
| 20 ~ 29, F | 30.03 | 75.60 |
| 30 ~ 39, M | 34.27 | 50.79 |
| 30 ~ 39, F | 18.75 | 78.93 |
| 40 ~ 49, M | 31.54 | 54.14 |
| 40 ~ 49, F | 26.25 | 79.81 |
| 50 ~ 59, M | 39.42 | 56.25 |
| 50 ~ 59, F | 20.26 | 89.37 |
| 60 ~ M | 35.66 | 50.30 |
| 60 ~ F | 30.38 | 67.65 |
| **Total** | **30.38** | **67.40** |

### 4.2 Prototype System of the Target Advertisement Service

In this section, we propose the result of prototype system of the target advertisement service based on the inference methods. As shown in Fig 4, the prototype system is consists of two parts, Client and Server. The server (Target advertisement Service Provider) contains a user profiling function and a broadcasting program delivering function. Client (User Interface) receives target advertisement contents. A user sends limited user's information to the prototype system, and the target advertisement service provider infers a TV viewers' profile based on the information and provides the target advertisement.

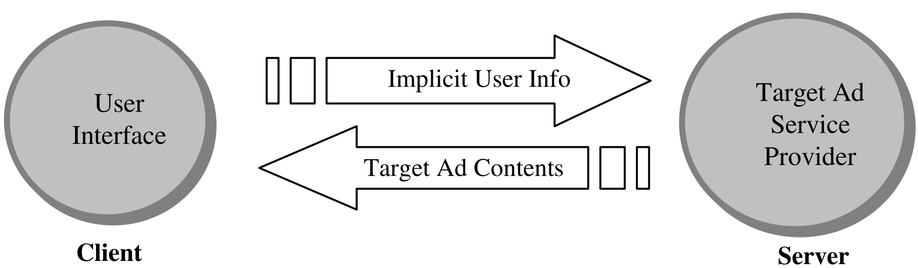
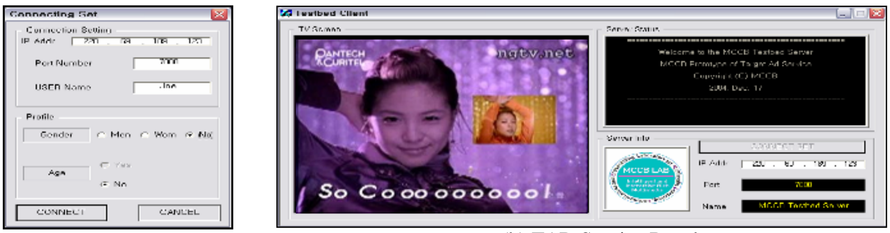



**Fig. 4.** Client and server in the target advertisement service

The experimental data for the prototype system of the target advertisement service used the free advertisement contents from NGTV (http://www.ngtv.net). We experimented with 28 advertisement contents and grouped those contents based on targeted ages and gender for the advertisement. When a client connects to a server, pop-up menu is displayed to receive the client's profile information. The pop-up menu enables 3 scenarios from Fig. 5 to Fig. 7. Fig. 5 (a) is the pop-up menu when the client connects to a server and provides nothing about ages and gender. Fig. 5 (b) is the result of prototype service. Since the client informs nothing about the client's profile, the server infers the client's gender and ages using vector correlation method and transmits the TAD contents to the client. The client user interface displays the received contents.




(a) Pop-Up Menu (b) TAD Service Result

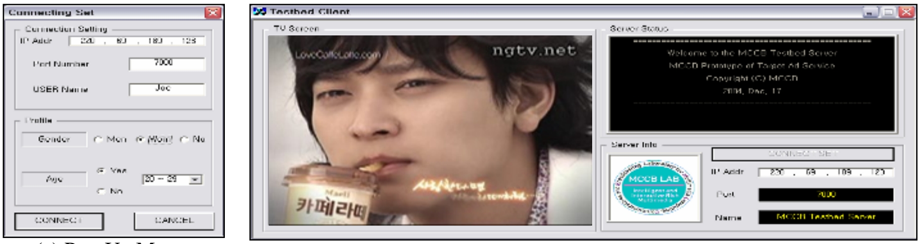
**Fig. 5.** The case that the server has no information about a TV viewer

We can see the inference result is women in 20s. The cell-phone advertisement for women in 20s is delivered to the client from the server. Fig 6 (a) is the pop-up menu when the client connects to a server and provides only the gender of a client. Fig 6 (b) is the result of prototype service. Since the client provides only about the client's gender, the server infers the client's ages using NDS method with the client's gender and TV usage history, and transmits the TAD contents to the client. The client user interface displays the received contents.


(a) Pop-Up Menu (b) TAD Service System

**Fig. 6.** The case that the server knows the gender of a TV viewer

Since the recommended ages is 20s, the server provides a fashion advertisement allocated for women in 20s. Fig 7 (a) is the pop-up menu when the client connects to a server and provides the gender (women) and age band (20s) of a client. Fig 7 (b) is the result of prototype service. Since the client informs about the client's gender and ages, the server does not have to infer the client's profile and transmits the TAD contents according to the client's given profile.




(a) Pop-Up Menu (b) TAD Service System

**Fig. 7.** The case that the server knows the gender and age band of a TV viewer

## 5 Conclusion

This paper proposed the target advertisement system using two TV viewers' profile inference methods; one is NDS method for inferring age band and the other is Inner product method for inferring age and gender together. In the experimental section, we implemented our method using real TV viewers' usage history and obtained about 70% accuracy when only gender information is known and about 77% accuracy when age and gender information is not known. The results are optimistic results for further studies about the target advertisement because only 1,764 viewers' usage history used for the training data is a too small data size. Also, we think our designed and implemented prototype of the target advertisement system can be the milestone for applying the system to practical use. For the future work, it is needed to improve our profile inference methods using larger size of the data than 1,764 viewers.

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