

Personalized TV-program Recommendation using Users' Viewing Histories and Time-Frames

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1. Introduction

In this paper, we propose a new recommendation algorithm called “time-frame watch-flow algorithm” for selecting the next K highest potential TV programs that a user might like based on the user's viewing history and a specific time-frame during a day. Based on our proposed method improving our previous proposal[1], the recommending value is assigned for each TV program according to the hypothesis that user's preference is dynamically being changed by time-frames in a day. Furthermore, the proposed method is also capable of giving a personalized recommendation for a specific user based on his/her watching sequence, improving the prediction accuracy and the diversity.

2. Proposed Model

2.1 Time-frame hypothesis

It is clear that user's preference toward a certain activity is affected by the time-frames during a day. For instance, some people tend to eat bread in the morning, rice at noon and drink beer in the evening. Thus, offering beer for the breakfast will likely be rejected. Moreover, if we can recognize the patterns of changing user's preference during a day, we can provide adaptive recommendation highly relevant to his/her preference. We consider that this concept is particularly useful in the IPTV environment where we know exactly when users start the service. Therefore, we can provide the better recommendation for users.

2.2 Time-Preference Calculation (tp_m)

The time-frame hypothesis motivates us to have a new parameter called time-preference value tp to measure each user's watching preference at a specific time-frame during a day. According to our hypothesis in time-frame, there are two factors changing user's preferences by time: one is TV program's features such as genre, actors, directors, and the other is the time length of each time-frame.

First, assuming that the time length for changing all users' preferences is in each t minutes, the total time-frames per a day are $(24 \times 60 / t)$ frames of equal length from 0h00' to 24h00'. For instance, if t is 30 minutes, we have 48 frames in total in a day calculated by $(24 \times 60) / 30$.

For the active user, we can assign the time-preference value to each time-frame by the equation (1). This equation takes into account the TV program's features, their weight and frequency.

$$tp_m = \frac{\sum w_i f_i}{\sum f_i} \quad (1)$$

Where, i is the feature of the TV program m , w_i is the weight of the feature i and f_i : the frequency of the feature i by the active

user.

The frequency of the feature i (f_i) is the number of feature occurrences in active user's history, and the weight of the feature i (w_i) is the average time spent for the feature decided by all the users in the dataset. Therefore, the weight (w_i) is calculated by equation (2):

$$w_i = \frac{\text{total time spent on } i}{\text{number of time } i \text{ occurred}} \quad (2)$$

2.3 The Time-frame Watch-flow Algorithm

The time-frame watch-flow algorithm takes into account both users watching sequences and TV programs' metadata. We assume that to the same TV program m , each active user u receive different recommending value r_m . r_m is defined as the likelihood estimation that active user will watch TV program m based on the previous one called *root*. Moreover, recommending value is associated with the time-preference tp_m and the similarity between m and *root* (*similarity*_{root,m}).

*similarity*_{root,m} is estimated by the sum of user-based-similarity *ubs*_{root,m} and metadata-based-similarity *mbs*_{root,m}. Consequently, recommending value of TV program m (r_m) is calculated by the below equation (3):

$$r_m = tp_m \times (ubs_{root,m} + mbs_{root,m}) \quad (3)$$

In order to discover the inclination in users' watching preferences, we need to learn from past watching histories to find out those components that a user likely prefers TV program m after a particular TV program selection. Therefore, we calculate the similarity between two TV programs *root* and m in the sum of two distinguish aspects: the user-based (*ubs*_{root,x}) and metadata-based (*mbs*_{root,x}) similarities. Hence:

$$\text{similarity}_{root,m} = \text{ubs}_{root,m} + \text{mbs}_{root,m} \quad (4)$$

The user-based similarity *ubs*_{root,x} defines the likelihood that users spend much time to watch m after *root*. Thus, we have to consider not only the probability of selecting m after *root* but also the time length consumed by m . According to the original conditional probability-based similarity[2], in order to calculate the similarity between two items, we extend the formula and apply it to the *ubs*_{root,m} by considering information of the TV program play-time of *root* and m , and user's explicit watching time of TV program m . The modified formula is shown in the equation (5) where α is a parameter that takes a value between 0 and 1.

$$\text{ubs}_{root,m} = \frac{\text{sum}_{root,m}}{(\text{sel}_{root}) \times (\text{sel}_m)^\alpha} \quad (5)$$

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Where, $sum_{root,m}$ is the total watching time of m when user already watched $root$, sel_{root} = number of selected $root \times$ play time of $root$ and sel_m = number of selected $m \times$ play time of m .

Additionally, the metadata-based similarity $mbs_{root,m}$ is calculated by TV program elements of $root$ and m . This value is utilized in order to find out the tendency of the next TV program's metadata elements after $root$ by considering the metadata elements in both $root$ and m . Therefore, the $mbs_{root,m}$ is calculated by equation (6):

$$mbs_{root,m} = \frac{intersection_{root,m}}{\# metadata elements} \quad (6)$$

Where, $intersection_{root,m}$ is the number of intersection of $root$ and m metadata elements.

Based on above analysis, we make the recommending value for every TV program by equation (7):

$$r_m = tp_m \times (ubs_{root,m} + mbs_{root,m}) \quad (7)$$

Finally, we can create a top-K recommending list by selecting the K top ranked TV programs from the list.

3. Experiments & Evaluation

3.1 Experimental Data

We evaluate our proposal using the data of user access to the WOWOW Website, where TV-program or movie information is provided for user watching. We take the specific Webpage watching featuring specific movie information by a user as a real TV program or movie watching by him/her in our experiments. It includes starting time and watching-time duration for each Webpage browsing, and also metadata for every TV program. Each user can be identified by a unique cookie without knowing his/her privacy.

3.2 Testing Methodology

We evaluate the proposal by top-K recommending list with $K = 5$ and 10 , and compare results with $t = 120$ (2 hours) and 180 (3 hours). Long users' watching sequences of 7 days are used for testing. The last TV program in each user sequence is taken for test set, and the rest is for training set. From the original data, we randomly choose 10 data groups in which each group contains 7 days data and more than 2000 users for the experiment. The final result is obtained by the average result of total 10 data groups.

3.3 Evaluation Metrics

We have 2 metrics to evaluate. The selecting rate shown in equation (8) measures the accuracy in selecting titles in K recommended titles. At a certain time, user can select only one title. Thus the highest selecting rate for $K = 5$ and 10 is 20% ($1/5$) and 10% ($1/10$), respectively. Moreover, as studied in [3] that we should also consider diversity in each recommending list, we have the coverage increasing measurement as in equation (9) calculating the fraction between the frequency of new features and the frequency of old features. New features are the relative complement of features in recommending list in user's historic features. The feature in the coverage is decided by the metadata components.

$$Selecting Rate = \frac{\# of hits in title}{K} \quad (8)$$

$$Coverage increasing = \frac{fre}{frequency_{user}} \quad (9)$$

Where, fre is the frequency of $(feature_{recommend} \setminus feature_{user})$, $frequency_{user}$ is the frequency of all features in user watching history.

3.5 Experimental Results

During 24 hours, we have 12 and 8 time-frames for 2 and 3 hours-time-frame in total, respectively. We take the center of each time-frame as its representative time in the horizontal axes to display our evaluation results shown in Figure 1. Through the experiments, both 2 and 3 hours-time-frame generate the similar curves, but 2 hours-time-frame provides better accuracy. Thus, the results show that the user's preference may be changed by less than 2 hours in a day. Furthermore, there is also relevance between the selecting rate and the coverage of the recommendations. Thus, we need to adjust recommending new programs to user not far from the user watching history in order to generate more accurate recommendation.

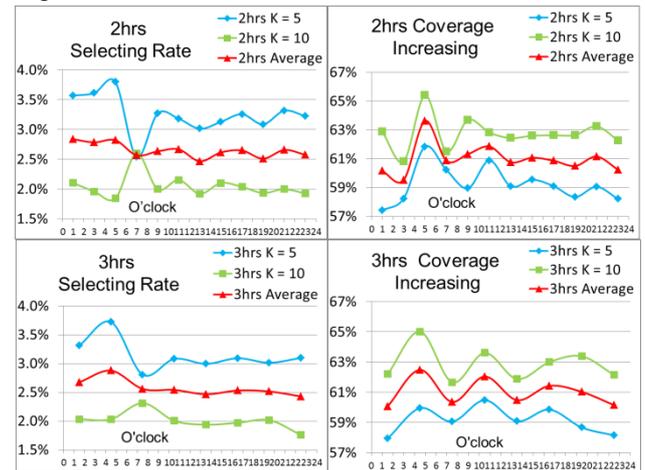


Figure 1. Selecting Rate and Coverage Increasing results in 2 and 3 hours-time-frame

4. Conclusion & Future Works

In this paper, we propose a time-frame model for detecting users' preferences. Our results suggest that users' preferences are changed by time-frame in a day, and we can still keep the high accurate selecting rate while diversifying the recommending list.

For our future work, we plan to expand the current experiment with longer time duration in each user watching sequence.

References

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