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Step-Enhancement of Memory Retention for User Interest Prediction

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ABSTRACT User behavior modeling and interest prediction are always the key elements in preference analysis, product recommendation and personalized service. The psychological memory theory has been proved capable of reflecting changes in user interest. However, merely focusing on the memory forgetting mechanism (the retention-only model) or considering the superimposition of interest retention in short term (the gradual-retention model), existing methods have a poor prediction capability because of ignoring the long-term impact of repeated behaviors. In this paper, we propose a step-enhancement of memory retention (SEMR) model which integrates the cross-enhancement-effects of multiple historical behaviors under different time windows to characterize user interest. In addition, we use some extended correction methods to eliminate the effect of discontinuous records. Numerical experiments using real TV viewing data validate the efficiency of our proposed model and methods, which reduce the average prediction error to 0.3, outperforming the traditional models by around 50%.

INDEX TERMS Memory enhancement, memory retention, user interest model.

I. INTRODUCTION

Along with the fast development of advertising algorithms and recommendation systems, analysis on user interest has become a key research topic in recent years. User behaviors conceal a large amount of information, which can be extracted and analyzed to improve user satisfaction and increase business profits through highly personalized services. Many researchers studied the changes of user interest over time [1]–[9], and the psychological memory theory [10], [11] has become a guiding method in analyzing interest forgetting.

Ebbinghaus' memory theory reflects the natural decay of human memory over time. Scholars used this theory to describe and predict user behaviors in multiple fields. As shown in Fig. 1(a), the real user behaviors are irregular with time. In user behavior analysis, the traditional retention-only model, as shown in Fig. 1(b), reflects how retention degree changes over time. However, this model is merely based on a single behavior and reflects the fading of interest only. It is well known that repeated behaviors promote user interest, hence the interest model is improved

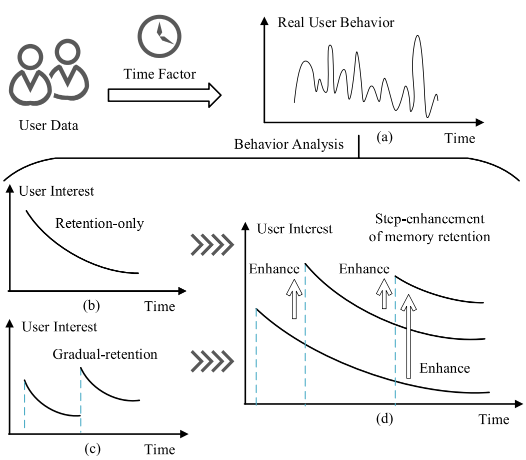

FIGURE 1. User interest model based on behavior analysis with time factor: (a) user's real behavior curve; (b) traditional retention-only interest model; (c) traditional gradual-retention interest model; (d) proposed step-enhancement of memory retention interest model.

by considering both the retention of the previous behavior and the superimposition of the current one. As shown in Fig. 1(c), the traditional gradual-retention model presents a gradual forgetting process with the emergence of user behaviors, instead

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TABLE 1. Related work summary.

Model type Function form	Retention-only Ebbinghaus forgetting curve	Retention-only Exponential function	Retention-only Power function	Gradual-retention Ebbinghaus forgetting curve	Gradual-retention Exponential function
Education	Chen *et al.* [12]				
Transportation			Shao *et al.* [13]		
Social network	Nan *et al.* [14]	Yu *et al.* [15], Gui *et al.* [16]			
Recommendation		Ding *et al.* [18], Zhang *et al.* [19] Zeng *et al.* [20], Zhu *et al.* [21] Zhang [22]	Yu *et al.* [17]	Koychev *et al.* [27]	Yin *et al.* [28]

of a monotonous downward trend. However, this improved model incorporates interest retention of adjacent behaviors in short term only and cannot describe the changes of user interest in long term. Therefore, we propose a step-enhancement of memory retention (SEMR) model to include the enhancement from historical behaviors in the description of user interest as shown in Fig. 1(d). One of the key contributions of our paper is that we construct an enhancement model taking into account the time intervals to reflect different influences produced by repeated behaviors, which can promote the research on the law of human memory enhancement. Because of the incorporation of interest retention with enhancement mechanism, the other key contribution of our SEMR model is that it can achieve a more precise prediction fit with the real user behaviors in the long term. Since the model is applicable to predict user interest of any field where user behavior has time-continuous measurability, the study of this paper is of great significance for improving user personalized recommendation services.

The structure of this paper is as follows. Section 2 gives the related literatures. Section 3 shows the details of our SEMR model and proposes two correction methods to eliminate the impact of discontinuous records caused by behavioral interruptions. Section 4 verifies our model's prediction ability by comparing the results with traditional methods and measures the improved performance due to two correction methods. Section 5 examines the sensitivity of time windows and explores the relationship between user interest trends and key parameters. Section 6 is the conclusion.

II. RELATED LITERATURE

Ebbinghaus memory theory [11], proposed by the German psychologist Hermann Ebbinghaus, discovered that human memory declines rapidly at the beginning of the forgetting process and then tends to be stable in the long term. This theory has been applied with success to many fields in various function forms as shown in Table 1. In the education field, Chen and Chung [12] studied the foreign language learning process and found that the vocabulary and grammar memorization practice method based on the memory retention cycle can promote learner's performance and interests. In the transportation field, Shao [13] presented a fading model to capture the driver's short-term memory on traffic signs, which helps to the design and management of the urban traffic system. In the social network field, researchers adopted different function forms of forgetting curves to predict user interest. For example, in [14], Nan *et al.* described the drift in user interest with the adoption of a linear forgetting function, where a time decay mechanism was introduced to improve the accuracy of article recommendation. In [15], Yu *et al.* implemented text classification and interest recommendation for Micro-blog users under the assumption of a negative exponential forgetting function. In [16], Gui *et al.* used a time node function to weight user interest on search engines at different times and made predictions by combining the LDA (Latent Dirichlet Allocation) model with multi-time factors.

In addition, memory theory has been widely used in recommendation system research, where various forms of retention functions were fitted to achieve collaborative filtering recommendation. In [17], Yu *et al.* considered user's short-term interests by introducing a power function to track user behaviors based on time windows. The most common used retention function is the exponential form [18]–[22]. In [18], Ding *et al.* introduced the personality decay factor in the retention curve to compute the decreasing time weights for user purchase interest based on their historical behaviors. Also using the personalized parameters, Zhang and Liu [19] proposed a time period partition algorithm to find recent interests of users by splitting their rating history into stages with different weights. In [20], Zeng *et al.* introduced the maximum and minimum time intervals in the retention function to modify the user-item rating matrix. In [21], Zhu *et al.* constructed a dynamic user interest model by introducing a time span into the exponent of the function, which divided linear time into time sequences to reflect changes in user interest. In addition, Zhang included both a time constant and a time factor into the function in user ratings during similarity calculations in [22].

In particular, most of the above-mentioned studies only considered memory retention theory for user interest analysis. However, user interest is influenced not only by memory forgetting, but also by memory enhancement caused by repetitive behaviors as pointed out in [23]. For example, cognitive psychologists found in [24] that students with spaced retrieval practice are more likely to get good scores in examinations than those with massed retrieval practice by studying the long-term memory retention of college students in learning mathematics, that is, the repetitive learning behavior helps to improve the long-term memory retention. Some attempts have been made to understand the memory enhancement mechanism in the biomedical field, where neural substrates [25] and sleep stages [26] were explored to study how to repair or improve the memory ability of the brain. At the same time, memory enhancement in user recommendation algorithms was also attempted. Koychev and Schwab [27] used the notion of gradual forgetting to reflect the effect of repetitive behaviors on user interest retention. Yin *et al.* [28] treated repetitive behaviors as the decay rate of memory forgetting in a multi-procedure time-effect quantization model. Although the influence of a new behavior on old interest retention is taken into account, these models only consider the increase of interest brought by two adjacent behaviors. Here the so-called enhancement is actually a simple addition of two retentions. To the best of our knowledge, no memory enhancement model has been proposed yet.

Therefore, the aim of our paper is to treat user's repeated behaviors as memory enhancement and explore how would it influence user interest under different time intervals by establishing a memory enhancement mechanism. Our team has been doing researches on media-related disciplines and cooperating with many TV network operators in China that offered a huge amount of available data. To our knowledge, TV users' viewing behaviors should follow human memory theory as well. Based on our previous studies in program prediction [29] and audience interest [30], we will explore the essential characteristic of TV user interest and analyze their viewing behaviors by combining the memory forgetting and the interest enhancement mechanism in the following sections.

III. STEP-ENHANCEMENT OF MEMORY RETENTION MODEL

A. TRADITIONAL USER INTEREST MODELS IN DIFFERENT FIELDS

As mentioned in Section 1, most of the previous researches on the modeling of user interest applied in different fields [17]–[22] only considered the forgetting process and ignored the potential enhancement brought by repetitive behaviors, where Ebbinghaus' forgetting curve [22], as shown in Fig. 2(a), was introduced in different function forms to consider time decay. Some researchers proposed improved models based on the idea of multi-procedure gradual forgetting [27] and treated the effect of user repeated behaviors to reduce the forgetting rate [28] as shown in Fig. 2(b), but they made no distinction between user behaviors occurring at different time intervals.

Both of the above-mentioned models are not general enough to reproduce the characteristics of user behavior. Since an event in the present is generally believed to have a bigger effect than an event in the past for future prediction, a natural improvement to the model is to consider user interest at different time intervals with different levels of enhancement effects. In our SEMR model, we consider both the interest retention and enhancement with a time-interval-effect coefficient and combine them by adaptive time windows to describe user interest in long term.

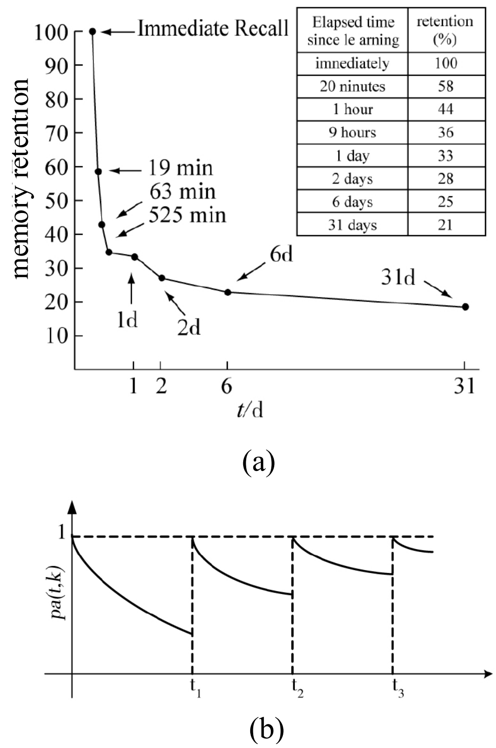


FIGURE 2. Traditional user interest models: (a) the retention-only model; (b) the gradual-retention model.

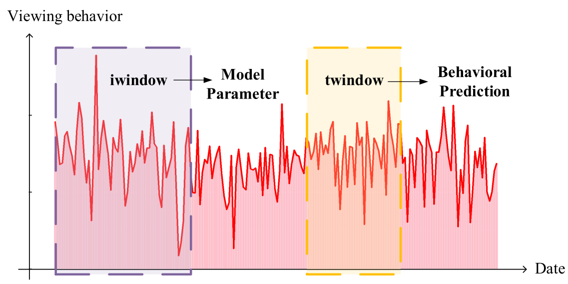


FIGURE 3. TV user's viewing behavior under two time windows (*iwindow* and *twindow*), where x-axis is the date and y-axis is the daily viewing duration index, and each viewing behavior is considered as an enhancement of interest while interest forgetting happens between every two viewing behaviors.

B. OUR STEP-ENHANCEMENT OF MEMORY RETENTION (SEMR) MODEL

1) THE IDEA OF SEMR MODEL

Most user behaviors in daily life are continuously measurable over time, such as the viewing behavior of TV users, which is the main topic of our research. Here we calculate the daily viewing duration of users as the behavior index to measure their interest. Fig. 3 shows that the fluctuation of the users' viewing behavior appears great repetitiveness and randomness, where user interest increases in the moment of the viewing and decreases until the next viewing occurs. To better capture the behavioral features of interest prediction, we propose a step-enhancement of memory retention (SEMR) model, in which two time window variables have significant impact on prediction results. One is the interest formation period *iwindow* which denotes the volume

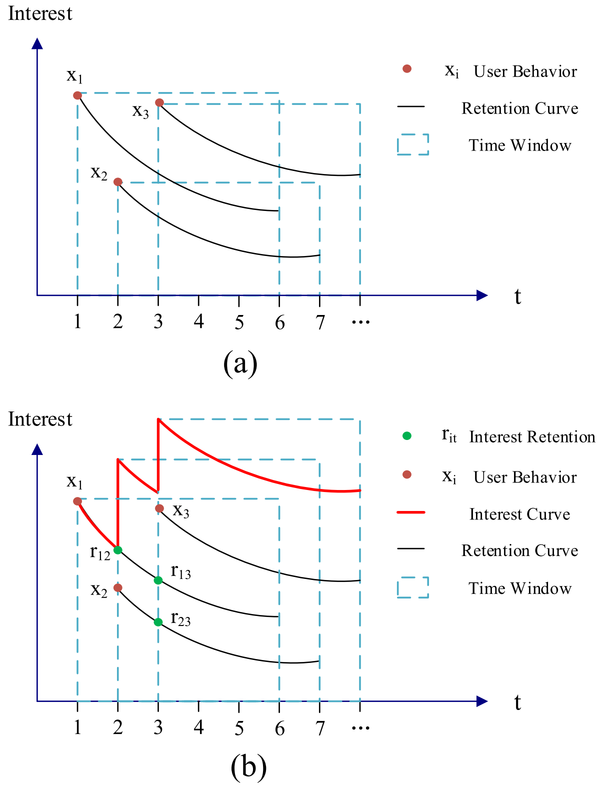


FIGURE 4. **The diagram of our SEMR model: (a) the forgetting process of SEMR model, where independent interest retention curves can be drawn by each user behavior x_i within the valid time window; (b) the enhancement process of SEMR model, where the user interest curve can be drawn by accumulating the user behavior x_i on a certain day and all interest retention r_{it} of previous days within the valid time window. Here x-axis is the time variable in days and y-axis is the user interest represented by behavioral index.**

of daily data required to estimate the model parameters, and the other is the memory time window *twindow* which denotes the volume of daily data used for prediction.

An important distinction between our SEMR model and traditional models is that we propose a time-interval-based enhancement mechanism, which is independent of the forgetting mechanism, to reflect the influence of multiple behaviors within the valid time window on the user interest. To decompose the interest prediction problems into multiple behavioral studies, we first regard different behaviors as unrelated events and calculate their interest according to the retention model, as shown in Fig. 4(a). Then, we combine the interest retentions of all these historical behaviors within the time window according to the enhancement model and obtain the ultimate interest at each specific moment as shown in Fig. 4(b).

Our proposed SEMR model is defined as follows:

$$I(t) = \sum_{\tau=\max(1,t-T)}^{t-1} R(t_r) \cdot E(t_e) \cdot x(\tau), \tag{1}$$

where the user interest $I(t)$ at time t is the accumulation of interests generated by all historical behaviors within the given time window T; $R(t_r)$ is the retention coefficient calculated from the retention function at time $t_r = t - \tau$; $E(t_e)$ is the enhancement coefficient describing the process of interest enhancement, which can be calculated from the enhancement function at time $t_e = t - \tau - 1$; and $x(\tau)$ is the behavioral index at time τ which ranges between $\max(1, t-T)$ to $t-1$.

In the following subsections, we give the detailed definitions of the retention function $R(t_r)$ and the enhancement function $E(t_e)$ in the SEMR model (1), which are two key components to achieve user behavior prediction.

TABLE 2. **The data from Ebbinghaus's experiment.**

Distance	0	1	2	3	7	14
x_a	33.3%	10.8%	7.0%	5.8%	3.3%	0.5%

2) RELATED MEMORY RETENTION AND ENHANCEMENT ALGORITHM

- The Retention Algorithm of SEMR Model
  Ebbinghaus' memory theory describes the natural decay of human memory or interest over time. Here, we describe the user interest decay following this theory by using the memory retention function in [11] as follows:

$$b = \frac{100k}{(\log_{10} t)^c + k}, \tag{2}$$

  where b is the memory retention, t is the learning interval, c and k are two constants that influence the decreasing speed of the memory retention curve.
  By converting the time interval from minute to day units and normalizing the memory retention, we get the interest retention function $R(t_r)$ as follows, which is one of the sub-models of our SEMR model:

$$R(t_r) = \frac{k}{(\log_{10}(1440 \cdot t_r))^c + k}, \tag{3}$$

  where t_r is the time interval.
- The Enhancement Algorithm of SEMR Model
  One contribution of this paper is the establishment of a time-interval-based enhancement function, which has not been considered by many researchers. In [11], Ebbinghaus realized the importance of repetitive learning on memory and conducted a recombination syllable memory experiment, from which he found that the correlation between interval items decreases with the distance increases.
  We use the same data source from [11] as shown in Table 2 and explore the interaction between behaviors in different time intervals. Note that in our case, the unit interval *Distance* used in [11] is converted to the time interval t by the following formula:

$$v(t) = \frac{x_a(Distance)}{x_a(0)} \cdot 100\%, \tag{4}$$

  where $v(t)$ is the interaction index (i.e. the enhancement function) calculated by the actual data $x_a(Distance)$ of Ebbinghaus' syllable experiment and t equals *Distance*. For analysis convenience, we further fit the discrete function $v(t)$ into the negative exponential form to get the

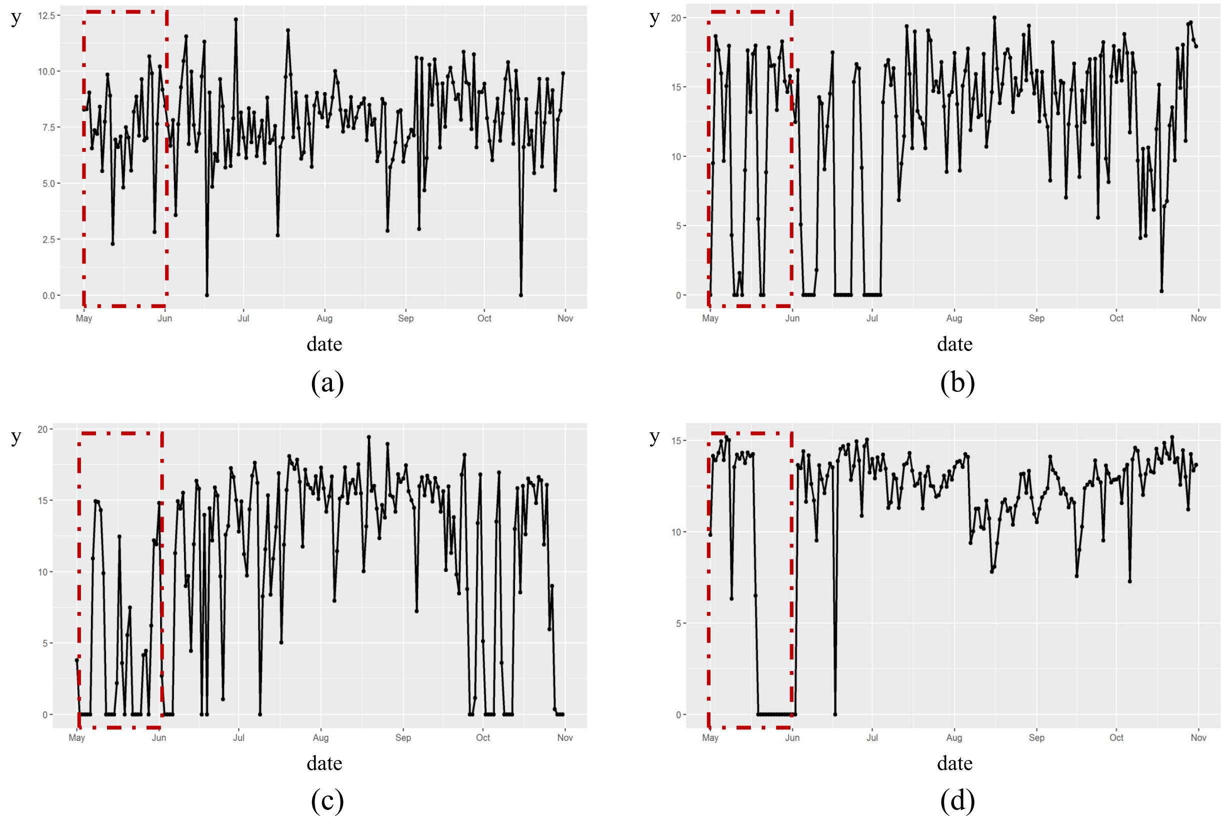


FIGURE 5. User behavior classification: (a) no behavioral interruption during interest formation period; (b) multiple short-term interruptions during interest formation period; (c) multiple long-term interruptions during interest formation period; (d) one long-term interruption during interest formation period; where y-axis is the daily viewing duration, the black line depicts the user's behavior and the red dotted box represents the interest formation period.

interest enhancement function $E(t_e)$ as follows, which is the another sub-model of our SEMR model:

$$E(t_e) = h \cdot e^{-t_e} + d, \tag{5}$$

where $E(t_e)$ is the degree of enhancement depends on different time interval t_e; h and d are two constants to be determined experimentally, and their sum should be close to 1.

3) THE SEMR MODEL

Given the retention model $R(t_r)$ in (3) and the enhancement model $E(t_e)$ in (5), we rewrite our SEMR model defined in (1) as follows:

$$I(t) = \sum_{\tau=\max(1,t-T)}^{t-1} \frac{k}{(\log_{10}(1440 \cdot (t-\tau)))^c + k} \cdot (h \cdot e^{\tau-t+1} + d) \cdot x(\tau), \tag{6}$$

where $I(t)$, t, $x(\tau)$, τ, and T are defined in (1); c and k are defined in (3); h and d are defined in (5).

In our SEMR model, the parameters k, c, h, and d are estimated using the least square (LS) algorithm [31]:

$$LS = \sum_{(t,\tau)=1}^{n} |I(t) - x(\tau)|^2, \tag{7}$$

where $I(t)$ is the predicted user interest at time t, $x(\tau)$ is the user's real behavioral index at time $\tau = t$, and n is the total number of a user's valid behavior days.

C. IMPROVED SEMR MODEL WITH INTERRUPTION CORRECTION

We classify the users into four typical types according to their viewing behaviors in the interest formation period as shown in Fig. 5. In order to ensure the performance of our interest model, we hope that each user has a complete continuous viewing records during their interest formation period just like the user shown in Fig. 5(a), but the reality is that user behaviors always present long or short interruptions due to some external factors which are not related to user interest, for example some short-term interruptions as shown in Fig. 5(b) may due to a power outage, and some long-term interruptions as shown in Fig. 5(d) may be caused by a business trip or other unknown reasons. As the behavioral interruptions during the interest formation period do not lead to the necessary interruptions in the subsequent forecast period, these absent records cannot be treated as the lack of user interest.

In order to reduce the impact of behavioral interruptions, we propose two correction methods to improve the prediction accuracy of our SEMR model based on discontinuous records. One is the average correction method as shown in Fig. 6(a), where the zero-values are replaced by the average

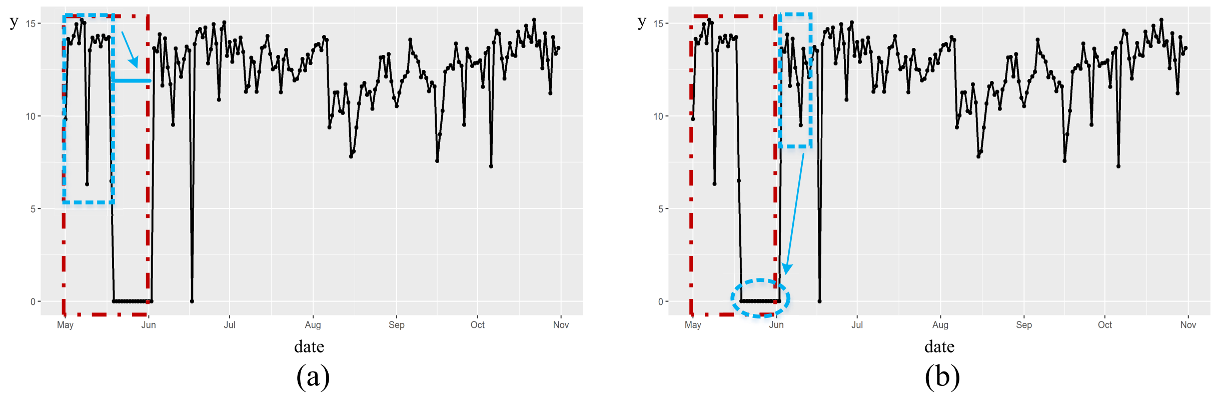


FIGURE 6. **Predictive correction methods for behavioral interruption: (a) average correction method; (b) extension correction method; where the black line depicts the user's behavior, the red dotted box represents the interest formation period and the blue one represents the correction method.**

values of all valid records within the interest formation period. As we can see, user behavior curve fluctuates around an invisible average line, and this is because the user interest has a stable level. Therefore, it is feasible to take the average value of valid records to replace the absent records, based on which the user interest can be modeled without deviating from its basic interest level too far. The average correction method can be expressed by the following formula:

$$x(\tau) = \begin{cases} x(\tau), & x(\tau) \neq 0 \\ \dfrac{\sum_{t=1}^{iwindow} x(t)}{n_0}, & x(\tau) = 0, \end{cases} \tag{8}$$

where $x(\tau)$ is the user behavioral index with τ ranges from 1 to *iwindow*, and n_0 is the total number of days on which the record is not zero.

However, when encountering a long-term behavioral interruption, the average correction method replaces continuous zero-values with continuous average values, thus this method is not conducive to reflect the changes of user interest either. Therefore, we propose an extension correction method as shown in Fig. 6(b). The extension correction method deletes days with zero-values and uses the subsequent days with non-zero-values to fill it forward. This method is based on the assumption that the user interest remains unchanged during the behavioral interruption, and when the user behavior continues, the interest also resumes. The extension correction method can be expressed by the following formula:

$$x(\tau) = \begin{cases} x(\tau), & x(\tau) \neq 0 \\ x(\tau + n'), & x(\tau) = 0, \end{cases} \tag{9}$$

where $x(\tau + n')$ denotes the next non-zero value of x after time τ.

So far we have established our SEMR model completely and improved it by supplementing the interruption correction mechanism. Here we developed a SEMR algorithm to give the application steps of our proposed model and explain how we use the equations to predict user behaviors as shown in Algorithm 1. First, the input user behavior data need to be processed by interruption correction, which uses (8) or (9) to eliminate the discontinuous records. Then the parameter estimation and time window optimization are realized by (7) within the interest formation period to build the personalized user interest model, based on which the behavioral prediction is finally achieved by (6).

Algorithm 1 SEMR

Input: user behavioral index $x(\tau)$
Output: predicted user interest $I(t)$

Initialization: c, k, h, d, *twindow*, *iwindow*;
for τ *from* 1 *to iwindow* **do**
  Interruption correction by equation (8) or (9);
end
for t *from* 2 *to iwindow* **do**
  Calculate user interest $I(t)$ by equation (6) where T = *twindow*;
  Estimate parameters c, k, h, d and optimize *iwindow* and *twindow* by equation (7);
end
for $t >$ *iwindow* **do**
  Predict user interest $I(t)$ by equation (6) with estimated parameters and optimal time windows;
end

IV. NUMERICAL EXPERIMENTS

A. PREDICTION CAPACITY OF SEMR MODEL

The effectiveness of our SEMR model is verified in this section by comparing its prediction error with two types of traditional models. One is the retention-only model constructed in [17]–[22], which only considers the forgetting of a single behavior using different forms of retention functions. Here we calculate the user interest of this first model type by $I(t) = R(t_r) \cdot x(\tau)$. The other is the gradual-retention model established in [27] and [28], which takes into account the overlapping influence of both the previous behavior and the subsequent behavior. Here we calculate the user interest of this second model type by $I(t) = R(t_r) \cdot (I(\tau) + x(\tau))$. The data used in this paper describes the viewing record of 100,000 TV users in one city of China, provided by a telecom company. Here we predict user

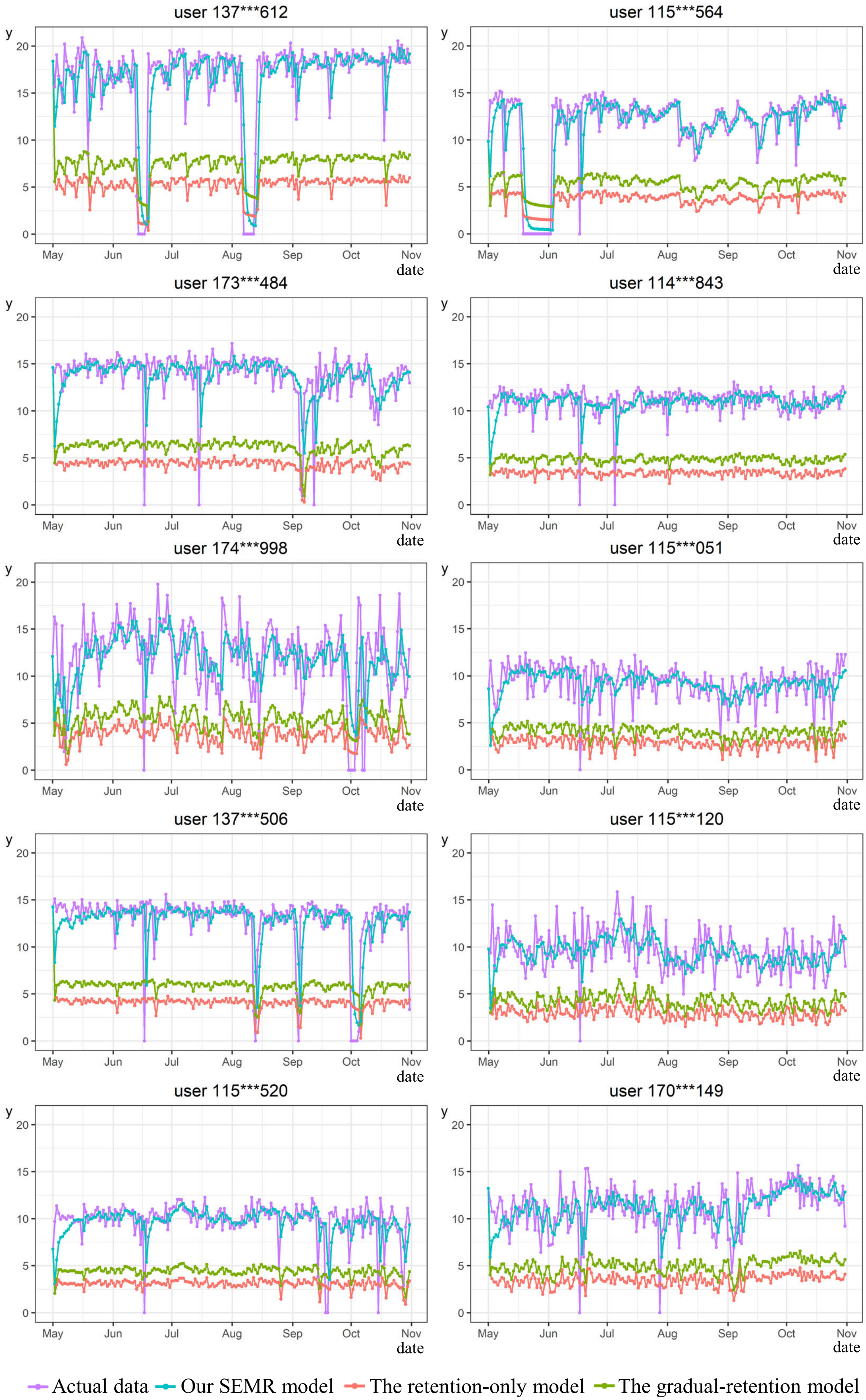


FIGURE 7. Comparison of our SEMR model with traditional models, where x-axis is the date and y-axis is the daily viewing duration (in hours).

behaviors based on their daily viewing duration (in hours) by use of different interest models (the retention-only model, the gradual-retention model, and our SEMR model with estimated parameters). We randomly select ten users from those

TABLE 3. The comparison of the average prediction errors of different users under different models.

User Type	Traditional retention-only model	Traditional gradual-retention model	Our SEMR model with parameter estimation
Stable	0.674	0.557	**0.230**
Fluctuating	0.664	0.564	**0.406**
Interruption	0.659	0.550	**0.302**
No-interruption	0.679	0.560	**0.289**

who often watch TV to give the comparison plots between the actual data and predicted data of three models as shown in Fig. 7, where user ID is partly hidden to protect privacy.

We can see from Fig. 7 that our SEMR model outperforms the traditional models that only consider memory forgetting or gradual retention with simple enhancement in short term. This advantage applies to different user groups as well, including users with stable (User 114***843) or fluctuating (User 174***998) behavior habits, and users with occasional (User 137***506) or long-term (User 115***564) behavioral breaks. In addition, the SEMR model has the potential of identifying and reacting to the sudden behavioral interruption with a higher prediction accuracy.

In order to verify the prediction capacity of our SEMR model and its applicability to different types of users, we classify all users according to their viewing habits (stable or fluctuating) and viewing continuity (interruption or no-interruption), and compare the average prediction errors of these users under different interest models as shown in Table 3. The average relative error δ is calculated by:

$$\delta = \frac{\sum_{t=1}^{n} \frac{|Pre(t)-Act(t)|}{Act(t)}}{n}, \tag{10}$$

where $Pre(t)$ is the predicted user interest and $Act(t)$ is the actual behavioral index, and n is the total number of viewing days.

Table 3 shows that our SEMR model always presents the best predictive ability (written in bold) for all types of users, which reduces the average error to around 0.30 comparing to the traditional retention-only model (around 0.67 by 55%) and the traditional gradual-retention model (around 0.56 by 46%). Therefore, the prediction capability of user interest model is proved to be successfully improved by introducing a time-interval-based enhancement mechanism and long-term time windows into our proposed SEMR model. In particular, we compare the model effect of different types of users, and the predictive accuracy of users with stable viewing habits is significantly higher than those who not, and the interruptions during the viewing process do cause a decline in predictive accuracy. Hence our proposed SEMR model is more precise for predicting behaviors of users with stable interests, which actually account for the vast majority of all TV users.

B. CORRECTION EXPERIMENT FOR BEHAVIORAL INTERRUPTION

Selecting users with discontinuous viewing records in the first month, we make predictions and compare the predictive errors of corrected methods with the uncorrected method.

TABLE 4. Error comparison of two correction methods.

User ID	No correction δ	Average correction δ	Average correction Improvement	Extension correction δ	Extension correction Improvement
115***479	0.536	0.491	8.38%	**0.416**	**22.42%**
137***762	0.151	0.131	12.92%	**0.130**	**13.83%**
137***530	0.716	0.658	8.16%	**0.631**	**11.92%**
115***564	0.110	0.100	9.55%	**0.100**	**9.59%**
115***883	0.407	0.386	5.26%	**0.374**	**8.07%**
137***349	0.228	0.227	0.60%	**0.224**	**2.09%**
137***741	0.257	**0.236**	**8.03%**	0.242	5.56%
174***474	0.432	**0.406**	**5.99%**	0.408	5.53%
137***794	0.215	**0.205**	**4.74%**	0.205	4.65%
115***218	0.247	**0.243**	**1.68%**	0.244	1.37%
......	......	......	......	......	......

Here we also give ten user results as the example in Table 4, where *iwindow* is set as one month and *twindow* adaptively takes the prior optimal value.

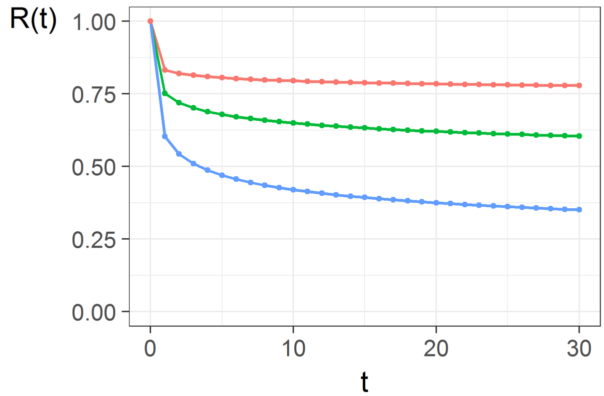
Table 4 shows that both correction methods reduce the prediction error but their performance has difference among users. In the table, the numbers written in bold denote the most effective method for a specific user. The correction effect of the extension method (up to 22% improvement) proves to be more effective overall than that of the average method (up to 13% improvement). Important to note is that the interruption correction is more effective for users with long-term behavioral interruptions during the interest formation period and the improvement is directly related to the length of the interruption. Furthermore, experiments with different prediction periods also indicate that both correction methods perform well in a short prediction range.

V. EXTENDED EXPERIMENTS

A. USER BEHAVIOR TENDENCY ANALYSIS

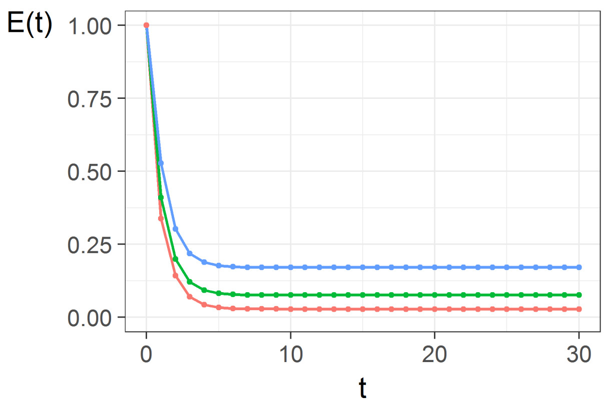
In this section, we explore the relationship between the parameters c, k, h, and d in our proposed model and user interest tendency. At first, we divide users into three groups according to their viewing trend: UP (indicates the users whose behavioral indexes show a general upward trend), DOWN (indicates the users whose behavioral indexes show a general downward trend), and STEADY (indicates the users whose behavioral indexes are generally stable). We then estimate parameters c, k, h, and d using the least square method (7) and plot the corresponding retention and enhancement curves in Fig. 8.

In these plots, we note that the estimated values of parameters c, k, h, and d decrease with the change of user behavioral index from UP to STEADY, and to DOWN, i.e. among the three user groups, the DOWN user interest decays the slowest, whereas the UP user interest decays the fastest. However, user interest enhancement is increasing when the behavioral index increases. This finding reflects the fact that users usually forget quickly and have a low retention level during the establishment of interest, but they are more susceptible to new stimuli and their interests tend to increase rapidly after repeated behaviors. On the other hand, it is difficult to re-promote interest enhancement for users in a period of decreasing interest. It is therefore possible to predict user interest tendency by analyzing the change of model parameters over time. For example, if model parameters are



user type	*c*	*k*
UP	2.695	33.707
STEADY	1.775	23.233
DOWN	0.901	13.971

(a)



user type	*h*	*d*
UP	0.971	0.171
STEADY	0.909	0.076
DOWN	0.843	0.028

(b)

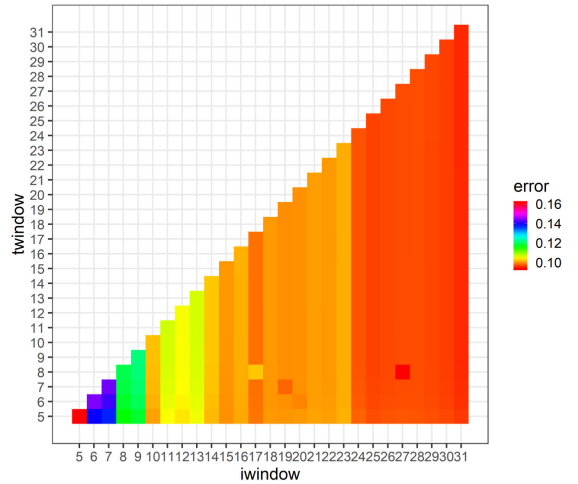
FIGURE 8. The comparison of estimated parameters in three different user groups: (a) parameters *c* and *k* in the retention curve; (b) parameters *h* and *d* in the enhancement curve.

decreasing for a particular user in a certain period, we infer that the user interest is also decreasing in that period.

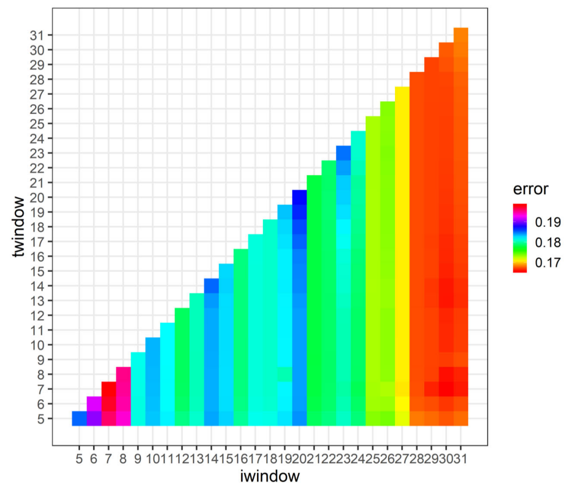
In addition, we also examine the model prediction effects for three types of users. Table 5 gives the maximum (Max), average (Ave), and minimum (Min) values of the average relative errors among the UP, DOWN, and STEADY users, with the optimal result written in bold. As can be seen from the table, our model has similar performance on different types of users, and its outperformance in STEADY users validates the conclusion of previous experiments that the application of our SEMR model is most effective for users with stable interests.

TABLE 5. Comparison of model prediction effects for different types of users.

User Type	Prediction Error Max	Prediction Error Ave	Prediction Error Min
UP	0.5241804	0.3367960	0.1892714
STEADY	0.5815037	**0.2833060**	**0.0852017**
DOWN	**0.4499912**	0.3164391	0.1289315



(a)



(b)

FIGURE 9. Synergistic time window experiment: (a) prediction error under different time windows for users with stable behavioral habits; (b) prediction error under different time windows for users with fluctuating behaviors, where *iwindow* changes from 5 (minimum data volume requirement of parameter estimation) to 31 (Ebbinghaus's experimental value), and *twindow* ≤ *iwindow*.

B. TIME WINDOW ANALYSIS

In our SEMR model, the interest formation period *iwindow* and the memory time window *twindow* respectively are crucial in determining the model parameters and the interest accumulation, and hence they both influence the prediction error. An example is shown in Fig. 9, where we see that the influence of *iwindow* on the prediction error is much bigger than that of *twindow*, and different users have different optimal interest formation periods and memory time windows. We conduct further sensitive experiments on *iwindow* and *twindow* separately:

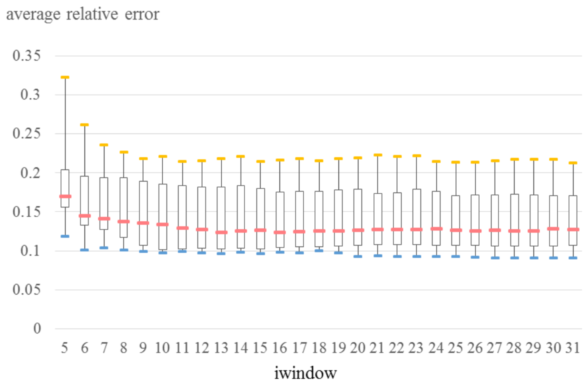


FIGURE 10. **The prediction error of user's interest under different *iwindow*, where y-axis is the average relative error, x-axis is the interest formation period *iwindow*, and *twindow* is always set as the best memory time window.**

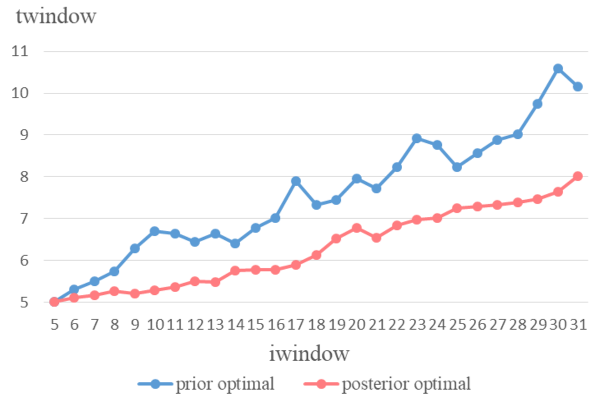


FIGURE 11. **Prior and posterior optimal *twindow* (y-axis) under different *iwindow* (x-axis).**

- Experiment 1: *iwindow* experiment
  This experiment is performed to give the minimum data volume required for building user interest model with the smallest prediction error. Fig. 10 is the box plot of prediction error of user interest under different choices of *iwindow*, showing that the longer the interest formation period is, the smaller the overall prediction error is. When *iwindow* reaches a certain length, the prediction error approaches stable and cannot be reduced any further, so we treat user interest at this threshold *iwindow* length as fixed. Here we find that users with stable behavioral habits reach this fixed stage sooner than those who have fluctuating behaviors as we would expect. On the whole, we need around fourteen days of data to understand the TV user's interest and reasonably predict his future behavior.
- Experiment 2: *twindow* experiment
  The second experiment is conducted to find the optimal *twindow* under different choices of interest formation period *iwindow*. i.e. we search for the appropriate volume of daily data required for user behavior prediction. We select the optimal *twindow* by minimizing the error between the predicted and the actual value. The prior optimal *twindow* is derived from the training dataset, while the posterior optimal *twindow* is derived from the test dataset.
  Fig. 11 shows the average stability length of optimal *twindow* results of all users, from which we can see that both the prior and posterior optimal *twindow* have a certain correlation with the length of interest formation period. The longer the *iwindow* is, the larger the corresponding optimal *twindow* is, which ranges from five to ten days with the posterior *twindow* smaller than the prior *twindow*.
  Based on these, we obtain some interesting results for the entire TV user group. The average prior optimal *twindow* for all users is around 7.5 days, while the average posterior is around 6.3 days. Combining together our findings, we conclude that the formation period of user interest is basically fixed up to 14 days, and the optimal *twindow* is around 6 days. That is, in the case of data lack or efficiency consideration, our proposed SEMR model requires at least 14 days of viewing data to analyze TV user interest and 6 days to make predictions. Similar procedures can be applied for different kinds of user data to understand what is the optimal amount of data required to successfully analyze and predict user behavior.

VI. CONCLUSION

In this paper, we propose a step-enhancement of memory retention (SEMR) model which takes into account the effect of memory forgetting as well as memory enhancement. Our developed SEMR model combines the memory retention model with an independent enhancement model to capture user interest based on the time interval, behavioral index and time window. The effectiveness of our proposed model is examined numerically by using actual viewing data of TV users in China, and experiments show that it outperforms other traditional models. Considering the possible discontinuous records, we further propose two correction methods to reduce the impact caused by behavioral interruptions. Experiments prove that both correction methods reduced the prediction error, especially for long-term behavioral interruptions. Then we estimate parameters and make sensitivity analysis under different time windows for different user types, which provide insights on the optimized application of our model.

The SEMR model proposed in this paper provides a preliminary yet important contribution for user interest description, whose predictive capacity is applicable to all general user behaviors with continuous measurability over time. In addition, the conclusions about parameters and time windows also provide some experience for the application of the SEMR model in other fields. A full understanding of the changing laws of user behavior is the basic step towards the analysis of the user comprehensive interest. In the future, we are planning to extend our research to analyze user interest considering multidimensional factors such as program labels and more behavioral indexes for program recommendation.

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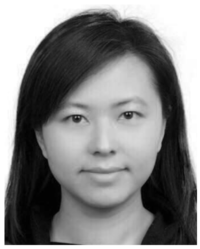

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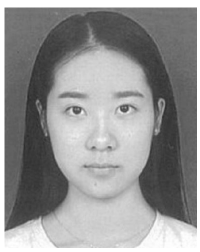

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