What to Do Next: Modeling User Behaviors by Time-LSTM

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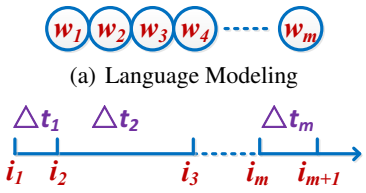
Abstract

Recently, Recurrent Neural Network (RNN) solutions for recommender systems (RS) are becoming increasingly popular. The insight is that, there exist some intrinsic patterns in the sequence of users' actions, and RNN has been proved to perform excellently when modeling sequential data. In traditional tasks such as language modeling, RNN solutions usually only consider the sequential order of objects without the notion of interval. However, in RS, time intervals between users' actions are of significant importance in capturing the relations of users' actions and the traditional RNN architectures are not good at modeling them. In this paper, we propose a new LSTM variant, i.e. Time-LSTM, to model users' sequential actions. Time-LSTM equips LSTM with time gates to model time intervals. These time gates are specifically designed, so that compared to the traditional RNN solutions, Time-LSTM better captures both of users' short-term and long-term interests, so as to improve the recommendation performance. Experimental results on two real-world datasets show the superiority of the recommendation method using Time-LSTM over the traditional methods.

1 Introduction

Recurrent Neural Network (RNN) solutions have become state-of-the-art methods on modeling sequential data. They are applied to a variety of domains, ranging from language modeling to machine translation to image captioning. With remarkable success achieved when RNN is applied to aforementioned domains, there is an increasing number of works trying to find RNN solutions in the area of recommender systems (RS). [Hidasi *et al.*, 2016a; Tan *et al.*, 2016; Hidasi *et al.*, 2016b] focus on RNN solutions in one certain type of recommendation task, i.e. session-based recommendations, where no user id exists and recommendations are based on previous consumed items within the same session. [Yu *et al.*, 2016] points out that RNN is able to capture users' general interest and sequential actions in RS and designs a RNN method for the next-basket recommendations. The insight that RNN works well in the above recommendation tasks is that, there exist some intrinsic patterns in the sequence of users' actions, e.g. once a man buys a badminton racket, he tends to buy some badmintons later, and RNN has been proved to perform excellently when modeling this type of patterns.



(a) Language Modeling

(b) Recommender Systems

Figure 1: w_m in (a) represents the m-th word. In (b), i_m represents the m-th consumed item and $\triangle t_m$ is the time interval between the time when i_m and i_{m+1} are consumed.

However, none of the above RNN solutions in RS considers the time interval between users' neighbour actions, while these time intervals are important to capture the relations of users' actions, e.g. two actions within a short time tend to be related and actions with a large time interval may aim at different goals. Therefore, it is important to exploit the time information when modeling users' behaviors, so as to improve the recommendation performance. We use Figure 1 to show what the time interval is and how it makes RS different from the traditional domains such as language modeling. Specifically, there is no notion of interval between neighbour words (e.g. no interval between w_1 and w_2) in language modeling, while there are time intervals between neighbor actions (e.g. $\triangle t_1$ between i_1 and i_2) in RS. Traditional RNN architectures are good at modeling the order information of sequential data as in Figure 1 (a), but they cannot well model time intervals in Figure 1 (b). Therefore, new models need to be proposed to address this problem.

A recently proposed model, i.e. Phased LSTM [Neil *et al.*, 2016], tries to model the time information by adding one time gate to LSTM [Hochreiter and Schmidhuber, 1997], where LSTM is an important ingredient of RNN architectures. In this model, the timestamp is the input of the time gate which controls the update of the cell state, the hidden state and thus the final output. Meanwhile, only samples lying in the model's active state are utilized, resulting in sparse updates during training. Thus, Phased LSTM can obtain a rather fast

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learning convergence in the training phase. However, there exist several challenges preventing Phased LSTM from becoming the best fit for recommendation tasks.

First of all, Phased LSTM models the timestamp, which is the characteristic of one single action, rather than the time interval between two actions. Hence, Phased LSTM may fail to properly model actions' relations. Secondly, users' action data is usually very sparse in most RS and Phased LSTM would ignore users' actions in its inactive state, which cannot make full use of behaviors' information for recommendations. Thirdly, previous studies [Jannach *et al.*, 2015] have pointed out that both of users' short-term and long-term interests are of great importance for recommendations, but traditional RNN architectures (including Phased LSTM) are not designed to distinguish and exploit these two types of interests simultaneously. Here, the *short-term interest* means that, the recommended items should depend on recently consumed items. For example, if a user just buys a Nikon camera, he is very likely to pick-up a memory card, lenses and protection cases in the near future. The *long-term interest* means that the recommended items should also be influenced by users' past actions, which reflect users' general interest.

To cope with the above challenges, we propose Time-LSTM, with three versions, to model users' sequential actions in RS. Actions' time intervals are modeled by time gates in Time-LSTM to capture actions' relations. The first version has only one time gate, which exploits time intervals to simultaneously capture the short-term and long-term interests. There are two time gates in our second version. One is designed to exploit time intervals to capture the short-term interest for current item recommendations and the other is to save time intervals to model the long-term interest for later recommendations. In the third version, we use coupled input and forget gates [Greff *et al.*, 2016] to reduce the number of parameters, making our model more concise. Time-LSTM with these time gates well captures users' short-term and long-term interests at the same time, so as to improve the recommendation performance. In addition, Time-LSTM has no inactive state to ignore actions, so that compared to Phased LSTM, it can make better use of behaviors' information. Our experimental results demonstrate the effectiveness of Time-LSTM. The contributions of this paper are as follows:

- Our proposed model, Time-LSTM, equips LSTM with carefully designed time gates, so that it is not only good at modeling the order information in sequential data, but can also well capture the interval information between objects. This is a general idea (not limited to RS) and other variants of Time-LSTM could be developed to model the event-based sequential data [Neil *et al.*, 2016] in other tasks. Note that different from Phased LSTM, which considers the timestamp and may implicitly capture the interval information, we explicitly model time intervals. In addition, compared to Phased LSTM, Time-LSTM exploits the information of more samples.
- We propose three versions of Time-LSTM. Compared to existing RNN solutions, these Time-LSTM versions can better capture users' short-term and long-term interests at the same time, so as to improve the recommendation performance.
- Our proposed models are evaluated on two real-world datasets, and the experimental results show the superiority of the recommendation method using Time-LSTM over traditional methods.

2 Ralated Work

2.1 LSTM and Its Variants

***LSTM*:** The commonly-used update equations [Graves, 2013] of LSTM are as follows:

$$i_m = \sigma_i(x_m W_{xi} + h_{m-1} W_{hi} + w_{ci} \odot c_{m-1} + b_i), \quad (1)$$

$$f_m = \sigma_f(x_m W_{xf} + h_{m-1} W_{hf} + w_{cf} \odot c_{m-1} + b_f), \quad (2)$$

$$c_m = f_m \odot c_{m-1} + i_m \odot \sigma_c(x_m W_{xc} + h_{m-1} W_{hc} + b_c), \quad (3)$$

$$o_m = \sigma_o(x_m W_{xo} + h_{m-1} W_{ho} + w_{co} \odot c_m + b_o), \quad (4)$$

$$h_m = o_m \odot \sigma_h(c_m), \quad (5)$$

where i_m, f_m, o_m represent the $input$, $forget$ and $output$ gates of the m-th object respectively. c_m is the cell activation vector. x_m and h_m represent the input feature vector and the hidden output vector respectively. Typically, σ_i, σ_f, σ_o are sigmoidal nonlinearities and σ_c, σ_h are tanh nonlinearities. Weight parameters W_{hi}, W_{hf}, W_{ho}, W_{xi}, W_{xf} and W_{xo} connect different inputs and gates with memory cells and outputs. b_i, b_f and b_o are corresponding biases. The update equation of c_m has two parts, one is a fraction of the previous cell state c_{m-1} that is controlled by f_m, and the other is a new input state created from the element-wise (Hadamard) product, denoted by $\odot$, of i_m and the output of the nonlinearity σ_c. The operation of input, forget and output gates can be further influenced by optional $peephole$ [Gers and Schmidhuber, 2000] connection weights w_{ci}, w_{cf}, w_{co}.

***Coupled input and forget gates*:** One variant of LSTM is to use coupled input and forget gates [Greff *et al.*, 2016] instead of separately deciding what to forget and what new information to add. It drops Eq. (2) and modifies Eq. (3) to:

$$c_m = (1 - i_m) \odot c_{m-1} + i_m \odot \sigma_c(x_m W_{xc} + h_{m-1} W_{hc} + b_c). \quad (6)$$

***Phased LSTM*:** Phased LSTM [Neil *et al.*, 2016] is a state-of-the-art RNN architecture for modeling event-based sequential data. It extends LSTM by adding the time gate k_m. k_m is controlled by three parameters: τ, r_{on} and s, where τ represents the total period of the model, s represents the phase shift and r_{on} is the ratio of the open period to the total period. τ, r_{on} and s are learned by training. k_m is formally defined as:

$$\phi_m = \frac{(t_m - s) \; mod \; \tau}{\tau},$$

$$k_m = \begin{cases} \frac{2\phi_m}{r_{on}}, & if \quad \phi_m < \frac{1}{2} r_{on}, \\ 2 - \frac{2\phi_m}{r_{on}}, & if \quad \frac{1}{2} r_{on} < \phi_m < r_{on}, \\ \alpha \phi_m, & otherwise, \end{cases} \quad (7)$$

where t_m is the timestamp and ϕ_m is an auxiliary variable. The gate k_m has three phases: k_m rises from 0 to 1 in the first phase and drops from 1 to 0 in the second phase (active state).

During the third phase, the model is in the inactive state. The leak rate α (close to 0 in training and equal to 0 in testing) is to propagate gradient information [He *et al.*, 2015]. Updates to c_m and h_m are permitted only in the active state. It rewrites Eq. (3) and Eq. (5) in LSTM to:

$$\tilde{c_m} = f_m \odot c_{m-1} + i_m \odot \sigma_c(x_m W_{xc} + h_{m-1} W_{hc} + b_c), \quad (8)$$

$$c_m = k_m \odot \tilde{c_m} + (1 - k_m) \odot c_{m-1}, \quad (9)$$

$$\tilde{h_m} = o_m \odot \sigma_h(\tilde{c_m}), \quad (10)$$

$$h_m = k_m \odot \tilde{h_m} + (1 - k_m) \odot h_{m-1}. \quad (11)$$

Due to the setting of inactive state, Phased LSTM cannot make full use of users' actions when applied to RS.

2.2 RNN Solutions in RS

[Hidasi *et al.*, 2016a; Tan *et al.*, 2016; Hidasi *et al.*, 2016b] focus on RNN solutions in session-based recommendations. [Hidasi *et al.*, 2016a] trains RNN with a ranking loss on one-hot representations of item-IDs in old sessions. The RNN is then used to provide recommendations on new user sessions. [Tan *et al.*, 2016] is an extension to [Hidasi *et al.*, 2016a], where it proposes two techniques, i.e. data augmentation and a method to account for shifts in the input data distribution, to improve the model performance. [Hidasi *et al.*, 2016b] considers a slightly different setting, where items' rich features exist. It introduces parallel RNN architectures to model clicks and items' features. [Yu *et al.*, 2016] designs a RNN method for the next-basket recommendations.

In this paper, we explore RNN solutions with a more common setting in the RS community, where we know the user id, but no session information is known. [Yu *et al.*, 2016] directly applies RNN to RS, without considering time intervals, while we add time gates to LSTM, which can exploit time intervals to improve the recommendation performance.

2.3 The Short-term and Long-term Interests

Most existing algorithms in RS, e.g. BPR (Bayesian Personalized Ranking) [Rendle *et al.*, 2009], matrix factorization [Koren *et al.*, 2009], tensor models [Zhao *et al.*, 2015], focus on modeling users' long-term interest, while the short-term interest seems to play a minor role in RS research. [Liu *et al.*, 2010] adapts a collaborative filtering approach to the user's current interest mined by content-based methods. Some approaches, e.g. [Aghabozorgi and Wah, 2009], [AlMurtadha *et al.*, 2010], apply collaborative filtering and association rules to match users' recent actions. [Jannach *et al.*, 2015] proposes that both of users' short-term and long-term interests are important in online shopping scenarios and quantifies several combining strategies. Semi-Markov Process (SMP) and Markov Renewal Process (MRP) [Janssen and Limnios, 2013] also aim at modeling sequential processes with time intervals. However, SMP and MRP cannot capture the long-term interest in our task, due to their Markov property.

3 Task Definition and Models' Adaptations

3.1 Task Definition

Let $U = \{u_1, u_2, \cdots\}$ be a set of users and $I = \{i_1, i_2, \cdots\}$ be a set of items. For each user u, his consuming history H^u is given by $H^u := [(i_1^u, t_1^u), (i_2^u, t_2^u), \cdots, (i_{n_u}^u, t_{n_u}^u)]$, where (i_m^u, t_m^u) means that u consumes his m-th item i_m^u at time t_m^u. Our task is to provide a list of recommended items $I_l \subseteq I$ given a certain user u_p at a certain time t_q.

3.2 Adaptations of LSTM and Phased LSTM

We adapt LSTM to our task in two ways. The first way is that, we simply record the sequence of items, regardless of the time information. Thus x_m in Eq. (1) is equivalent to i_m^u in our task. The second way considers the time information. We first transform H^u to $[(i_1^u, t_2^u - t_1^u), (i_2^u, t_3^u - t_2^u), \cdots, (i_{n_u}^u, t_q - t_{n_u}^u)]$. Then x_m is equivalent to $(i_m^u, t_{m+1}^u - t_m^u)$ in our task. For adaptations of LSTM and all its variants, the model's output is a probability distribution over all items calculated by h_m. The loss is based on the output and i_{m+1}^u. We use one-hot representations for i_m^u and one entry for $t_{m+1}^u - t_m^u$.

For Phased LSTM's adaptation, x_m in Eq. (1) is equivalent to i_m^u in our task. t_m in Eq. (7) is equivalent to t_{m+1}^u.

4 Time-LSTM

When applying LSTM and its variants to RS, x_m in Eq. (3) contains the information of the last item that a user consumed. Since this is the user's most recent action, we can exploit x_m to learn his/her current short-term interest. On the other hand, c_{m-1} contains the information of this user's previous actions, thus c_{m-1} reflects his/her long-term interest. However, to what extent x_m reflects current short-term interest varies in different situations, e.g. if x_m is consumed long time ago, it can hardly reflect current consuming goal. In Time-LSTM, we use time gates to control the influence of the last consumed item (x_m) on current recommendations. In addition, these time gates help to store time intervals in $c_m, c_{m+1} \cdots$, which reflect users' long-term interest in later recommendations. Therefore, not only previously consumed items, but also corresponding time intervals are considered when modeling users' long-term interest. Three versions of Time-LSTM are designed as follows.

4.1 Time-LSTM 1

This version adds one time gate T_m to LSTM, which is shown in Fig. 2 (a). Based on the update equations (Eq. (1)$\sim$(5)) of LSTM, we add one update equation for T_m as:

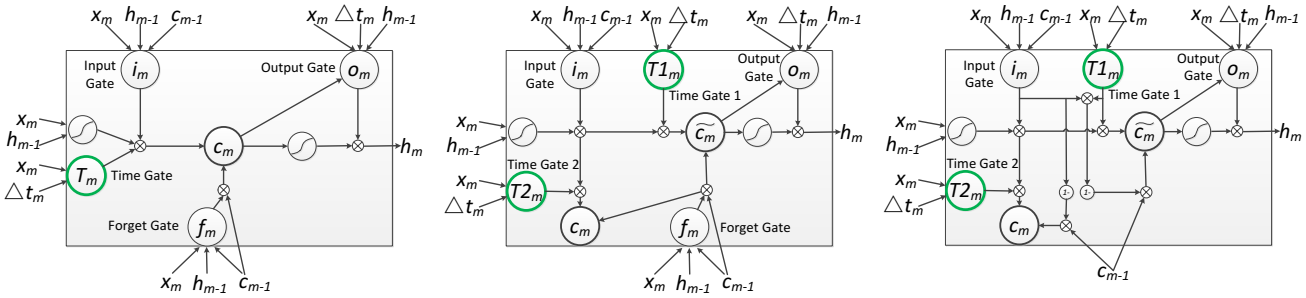
$$T_m = \sigma_t(x_m W_{xt} + \sigma_{\triangle t}(\triangle t_m W_{tt}) + b_t). \quad (12)$$

We then modify Eq. (3) and Eq. (4) to:

$$c_m = f_m \odot c_{m-1} + i_m \odot T_m \odot \sigma_c(x_m W_{xc} + h_{m-1} W_{hc} + b_c), \quad (13)$$

$$o_m = \sigma_o(x_m W_{xo} + \triangle t_m W_{to} + h_{m-1} W_{ho} + w_{co} \odot c_m + b_o). \quad (14)$$

$\triangle t_m$ is the time interval and $\sigma_{\triangle t}$ is a sigmoid function. T_m is helpful in two ways. As shown in Eq. (13), on one hand, $\sigma_c(x_m W_{xc} + h_{m-1} W_{hc} + b_c)$ is filtered by not only the input gate i_m, but also the time gate T_m. So T_m can control the influence of x_m on current recommendations. On the other hand, $\triangle t_m$ is firstly stored in T_m, then transferred to c_m, and would be transferred to $c_{m+1}, c_{m+2} \cdots$. Thus T_m helps to



(a) Time-LSTM 1 (b) Time-LSTM 2 (c) Time-LSTM 3

Figure 2: Model architectures of (a) Time-LSTM 1, (b) Time-LSTM 2 and (c) Time-LSTM 3. Time-LSTM 1 has one time gate T_m, which is mainly controlled by the time interval $\triangle t_m$ instead of the timestamp t_m. Time-LSTM 2 has two time gates, i.e. $T1_m$ and $T2_m$, where $T1_m$ is designed to exploit time intervals for current item recommendations and $T2_m$ is to store time intervals for later recommendations. Time-LSTM 3 uses coupled input and forget gates.

store $\triangle t_m$ to model users' long-term interest $(c_m, c_{m+1} \cdots)$ for later recommendations. Note that, in a similar way, we are able to generalize T_m to other RNN architectures, such as GRU [Cho *et al.*, 2014].

T_m is fully learned from data. However, as a priori knowledge, we know that given a certain last consumed item, if it is more recently consumed, it should have a larger influence on current recommendations. We want to incorporate this priori knowledge into the design of the time gate.

4.2 Time-LSTM 2

Two time gates, i.e. $T1_m$ and $T2_m$, are designed in this version. $T1_m$ is to control the influence of the last consumed item on current item recommendations, and $T2_m$ is to store time intervals to model users' long-term interest for later recommendations. The architecture is shown in Fig. 2 (b). Based on the update equations of LSTM, we first add two update equations for $T1_m$ and $T2_m$ as:

$$T1_m = \sigma_1(x_m W_{x1} + \sigma_{\triangle t}(\triangle t_m W_{t1}) + b_1), \quad s.t. \;\; W_{t1} \leq 0, \tag{15}$$

$$T2_m = \sigma_2(x_m W_{x2} + \sigma_{\triangle t}(\triangle t_m W_{t2}) + b_2). \tag{16}$$

We then modify Eq. (3)$\sim$(5) to:

$$\widetilde{c_m} = f_m \odot c_{m-1} + i_m \odot T1_m \odot \sigma_c(x_m W_{xc} + h_{m-1} W_{hc} + b_c), \tag{17}$$

$$c_m = f_m \odot c_{m-1} + i_m \odot T2_m \odot \sigma_c(x_m W_{xc} + h_{m-1} W_{hc} + b_c), \tag{18}$$

$$o_m = \sigma_o(x_m W_{xo} + \triangle t_m W_{to} + h_{m-1} W_{ho} + w_{co} \odot \widetilde{c_m} + b_o), \tag{19}$$

$$h_m = o_m \odot \sigma_h(\widetilde{c_m}). \tag{20}$$

Just as the input gate i_m in Eq. (17), $T1_m$ can be regarded as another filter, so that $\sigma_c(x_m W_{xc} + h_{m-1} W_{hc} + b_c)$ is filtered by not only i_m but also $T1_m$. We use a new cell state $\widetilde{c_m}$ to store the result, which is then transferred to the output gate o_m, the hidden state h_m and finally influences current item recommendations. $T2_m$ firstly stores $\triangle t_m$, then transfers it to c_m, and would transfer it to $c_{m+1}, c_{m+2} \cdots$ to model users' long-term interest for later recommendations. Thus in Eq. (18), $T2_m$ acts more as the role of $\sigma_c(x_m W_{xc} + h_{m-1} W_{hc} + b_c)$.

Through the constraint $W_{t1} \leq 0$ in Eq. (15), $T1_m$ can exploit the priori knowledge described in section 4.1 to control the influence of x_m on current item recommendations. Specifically, if $\triangle t_m$ is smaller, according to Eq. (15), $T1_m$ would be larger. Then according to Eq. (17), x_m would have a larger influence on current item recommendations (i.e. x_m better reflects the short-term interest, thus we increase its influence). On the other hand, if $\triangle t_m$ is larger, with a similar analysis, x_m would have a smaller influence and correspondingly c_{m-1} would more significantly affect current recommendations (i.e. we are more uncertain about the short-term interest, thus we increase the influence of the long-term interest). For $T2_m$, however, it doesn't make sense to impose such constraint on W_{t2} in Eq. (16) in terms of modeling users' long-term interest for later recommendations. This also explains why we design two time gates in this version, i.e. to distinguish and customize the role for current recommendations and the role for later recommendations.

4.3 Time-LSTM 3

Inspired by [Greff *et al.*, 2016], this version (Fig. 2 (c)) uses coupled input and forget gates. Specifically, based on Time-LSTM 2, we remove the forget gate, and modify Eq. (17) and Eq. (18) to:

$$\widetilde{c_m} = (1 - i_m \odot T1_m) \odot c_{m-1} + i_m \odot T1_m \odot \sigma_c(x_m W_{xc} + h_{m-1} W_{hc} + b_c), \tag{21}$$

$$c_m = (1 - i_m) \odot c_{m-1} + i_m \odot T2_m \odot \sigma_c(x_m W_{xc} + h_{m-1} W_{hc} + b_c). \tag{22}$$

Since $T1_m$ is regarded as a filter (similar to i_m), thus we replace the forget gate with $(1 - i_m \odot T1_m)$ in Eq. (21). $T2_m$ is to store time intervals (similar to $\sigma_c(x_m W_{xc} + h_{m-1} W_{hc} + b_c)$), thus we use $(1 - i_m)$ in Eq. (22). The difference between Time-LSTM 3 and [Greff *et al.*, 2016] lies in that (1) time gates exist in Time-LSTM 3 but not in [Greff *et al.*, 2016] and, (2) Time-LSTM 3 has one additional coupled gate and one additional cell state.

The way we adapt Time-LSTM to our task is similar to the second way of LSTM's adaptations. Firstly, we transform H^u to $[(i_1^u, t_2^u - t_1^u), (i_2^u, t_3^u - t_2^u), \cdots, (i_{n_u}^u, t_q - t_{n_u}^u)]$. Then x_m in Time-LSTM is equivalent to i_m^u in our task. $\triangle t_m$ is equivalent to $t_{m+1}^u - t_m^u$.

4.4 Training

The parameters in Time-LSTM models are optimized by AdaGrad [Duchi *et al.*, 2011], a variant of Stochastic Gradient Descent (SGD). For the constraint $W_{t1} \leq 0$ in Eq. (15), we use the projection operator described in [Rakhlin *et al.*, 2012] to handle it, i.e. if we have $W_{t1} > 0$ during training iterations, we reset $W_{t1} = 0$.

In real-world applications, users' new consuming actions are continually generated. Other users' consuming histories help to provide "collaborative information" for the target user's recommendations. Meanwhile, this user's previous consuming history can provide "personalized information" for his later recommendations. Thus we want to make use of all available consuming histories (including newly generated actions) for recommendations, i.e. an online learning setting [Zhao *et al.*, 2016]. To achieve this, we adapt the dynamic updated model in [Mikolov *et al.*, 2010] to our task as follows. Step one, our model is trained on users' existing consuming histories until convergence. Step two, we repeat following procedure: After n (increase n for efficiency) new actions being generated, we update previous parameters once by applying AdaGrad to users' updated consuming histories. We may repeat above two steps periodically. The period can be tuned considering both of the recommendation performance and computational cost.

5 Experiments

5.1 Datasets and Experiment Settings

Our proposed algorithm is evaluated on two datasets, *LastFM*[1] and *CiteULike*[2]. For the LastFM dataset, we extract tuples <*user_id, song_id, timestamp*>, where each represents the action that user *user_id* listens to song *song_id* at time *timestamp*. For the CiteULike dataset, one user annotating one research paper at a certain time may have several records, in order to distinguish different tags. We merge them as one record and extract tuples <*user_id, paper_id, timestamp*>. Note that different from works such as [Zhu *et al.*, 2016], tags are not exploited for recommendations in this paper. Users and items with few interactions are filtered. These tuples are organized by *user_id* and ordered by *timestamp*. Table 1 shows their statistics.

For each dataset, 80% users are randomly selected as training users and their tuples are used for training. The remaining users are test users. For each test user u, its ordered tuples $T^u := [(u, i_1^u, t_1^u), (u, i_2^u, t_2^u), \cdots, (u, i_{n'_u}^u, t_{n'_u}^u)]$ would generate $n'_u - 1$ test cases, where the k-th test case is to perform recommendations at time t_{k+1}^u given u's consuming history $[(i_1^u, t_1^u), (i_2^u, t_2^u), \cdots, (i_k^u, t_k^u)]$ with the ground truth i_{k+1}^u.

5.2 Compared Methods

We compare Time-LSTM to the following methods. The method in [Yu *et al.*, 2016] is not compared, because its setting is different from ours and some techniques, e.g. pooling operations, cannot be applied to our task.

[1]http://www.dtic.upf.edu/∼ocelma/MusicRecommendationDataset/lastfm-1K.html

[2]http://www.citeulike.org/faq/data.adp

Table 1: Statistics of Two Datasets

	LastFM	CiteULike
Number of Users	987	1625
Number of Items	5000	5000
Number of Actions	818767	35934

***CoOccur+BPR*:** This is a combining strategy proposed in [Jannach *et al.*, 2015], where CoOccur is to capture the short-term interest and BPR is to capture the long-term interest. Specifically, CoOccur ranks items by the conditional probability of item co-occurring in users' sessions (association rules). Other items are appended to the recommendation list (if it is not filled up yet) ranked by BPR. We do not use FeatureMatching and RecentlyViewed in [Jannach *et al.*, 2015]. The reason is that, FeatureMatching requires items' attribute information, which is not available in our task. RecentlyViewed simply recommends recently viewed items. However, in most cases, we want the RS to provide us with favorable items that we ignore, since even without the help of RS, we can still find items that we are familiar with (e.g. items that we recently viewed or comsumed). This method needs the session information. We use a commonly used approach, *timeout* [Huang *et al.*, 2004], to identify sessions in users' consuming histories.

***Session-RNN*:** This method [Hidasi *et al.*, 2016a] uses RNN to capture the short-term interest based on items within a session in session-based recommendations. The long-term interest is not considered. The session information is extracted as described in CoOccur+BPR. We use the publicly available python implementation[3] of Session-RNN.

***LSTM*:** The first way of LSTM's adaptation in section 3.2.

***LSTM+time*:** The second way of LSTM's adaptation in section 3.2.

***Phased LSTM*:** Phased LSTM's adaptation in section 3.2.

The dynamic updated model described in section 4.4 is applied to LSTM and its variants, where the tuples of training users are used to train the model for step one. A similar updating strategy is applied to CoOccur+BPR and Session-RNN to ensure fair comparisons. The number of units is set to 512 for LSTM and its variants. The other hyperparameters in all methods are tuned via cross-validation or set as in the original paper. Our code is publicly available[4].

5.3 Evaluations

Recall@10: Each target item i_g (ground truth) is combined with 100 other random items. These 101 items are then ranked by the method and the top 10 items form the recommendation list. Recall@10 is defined as:

$$Recall@10 = \frac{n_{hit}}{n_{testcase}}. \tag{23}$$

n_{hit} is the number of test cases where i_g is in the recommendation list and $n_{testcase}$ is the number of all test cases.

MRR@10 (Mean Reciprocal Rank): This is the average of reciprocal ranks of i_g in the recommendation list. The reciprocal rank is set to 0 if the rank is above 10. MRR@10 takes into account the rank of the item.

[3]https://github.com/hidasib/GRU4Rec

[4]https://github.com/DarryO/time_lstm

Each metric is evaluated 10 times and averaged. These two metrics are also used in [Jannach *et al.*, 2015].

5.4 Results and Discussions

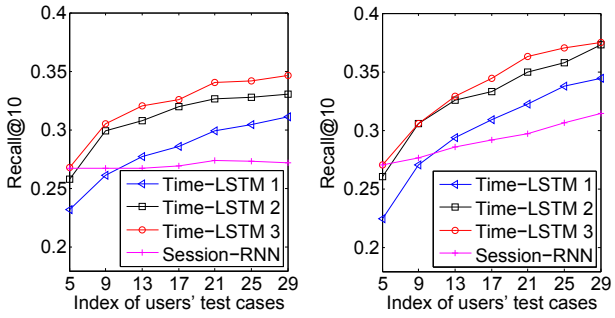
Method Comparison: As shown in Table 2, Time-LSTM models generally outperform other baselines. Time-LSTM 2 and Time-LSTM 3 have better performance than Time-LSTM 1, which demonstrates the effectiveness of using two time gates instead of one time gate. $T1_m = 1$ and $T2_m = 1$ are the results when we rewrite Eq. (15) to $T1_m = 1$ and Eq. (16) to $T2_m = 1$, respectively. They perform worse than the original version, which indicates that using our designed $T1_m$ to filter the input and $T2_m$ to store time intervals can both improve the performance. LSTM+time performs slightly worse than LSTM in CiteULike, which may be due to the usually large time intervals in CiteULike (after normalization, its performance improves, but is still worse than Time-LSTM models).
Performance on Cold and Warm Users: We regard users as cold if they have consumed few items and warm if the opposite. Due to space limitation, we only show the results of Recall@10 in LastFM. As shown in Figure 3, the index k in the x-axis represents the k-th test cases, where we predict test users' $(k+1)$-th actions given all the actions of training users and the first k actions of test users. (a) demonstrates that Time-LSTM performs better for warm users (larger indexes indicate that users have consumed more items). The reason is that with more actions contained in c_{m-1}, Time-LSTM can better model the long-term interest for recommendations. For cold users, the performance of Time-LSTM is comparable to that of Session-RNN. This is because that although with few consuming actions, Time-LSTM can still well perform recommendations by capturing the short-term interest. The performance in (b) is better than that in (a), which proves the effectiveness of the dynamic updated model. The performance improvement from (a) to (b) is more remarkable for warm users, because the model is updated more times when users are warm than when they are cold.
Number of Units and Efficiency: We vary the number of units (n_u) to see how the performance and training time change. The training time is evaluated on a GeForce GTX Titan Black GPU. Due to space limitation, we only show the results of Recall@10 and the training time in LastFM. As shown in Figure 4 (a), increasing n_u can improve Recall@10, but the improvement slows down or it even deteriorates when n_u is larger than 128. On the other hand, as shown in Figure 4 (b), the training time is continually increasing when n_u varies, and it is expensive to move from 512 units to 1024. Thus it is appropriate to assign [128, 512] to n_u. Time-LSTM 3 always has a less training time than Time-LSTM 2 when n_u varies. The reason is that the coupled input and forget gates in Time-LSTM 3 reduce the number of parameters and speed up the training process.

6 Conclusions

We propose Time-LSTM to model users' sequential actions in RS, where time intervals between neighbour actions are modeled by time gates in Time-LSTM. We design three versions of Time-LSTM, which well capture users' short-term and long-term interests at the same time, so as to improve the recommendation performance. Experimental results on two real-world datasets also show the effectiveness of Time-LSTM. In future work, we would design new versions of Time-LSTM to simultaneously model different types of behaviors in other application scenarios, e.g. click/collect/add-to-cart/pay-for in e-commerce platforms. In addition, our method cannot generate recommendations for users who have no actions. Inspired by [Wang *et al.*, 2016a; 2016b], we will explore the active learning solutions to this issue.

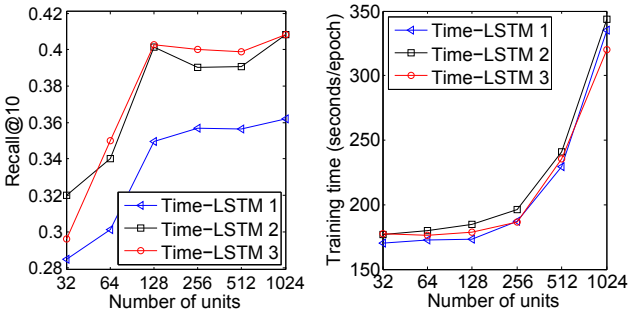
Table 2: Method Comparison

		LastFM		CiteULike	
		Recall@10	MRR@10	Recall@10	MRR@10
CoOccur+BPR		0.3217	0.1401	0.6954	0.2901
Session-RNN		0.3405	0.1573	0.7129	0.2997
LSTM		0.2451	0.0892	0.6824	0.2889
LSTM+time		0.2628	0.0977	0.6655	0.2831
Phased LSTM		0.2360	0.0859	0.6087	0.2539
Time-LSTM 1		0.3566	0.1853	0.7428	0.3179
Time-LSTM 2	original	0.3909	0.2250	0.7476	0.3377
	$T1_m = 1$	0.3236	0.1812	0.7058	0.3044
	$T2_m = 1$	0.3643	0.2073	0.7014	0.3105
Time-LSTM 3	original	**0.3990**	**0.2657**	**0.7585**	**0.3660**
	$T1_m = 1$	0.3742	0.2212	0.6874	0.3046
	$T2_m = 1$	0.3677	0.2249	0.7128	0.3232



(a) Without Dynamic Update (b) With Dynamic Update

Figure 3: Recall@10 evaluated on different indexes of users' test cases in LastFM. The dynamic updated model is applied in (b), but not in (a).



(a) (b)

Figure 4: (a) and (b) show how Recall@10 and the training time change when we vary the number of units in LastFM.

Acknowledgements

This work was supported by the National Basic Research Program of China (973 Program) under Grant 2013CB336500 and National Natural Science Foundation of China under Grant 61672409, 61379071, 61522206, 61373118. Also thanks to Prof. Xifeng Yan and his students in UCSB.

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