Time Weight Content-based Extensions of Temporal Graphs for Personalized Recommendation

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Abstract: Recommender systems are an answer to information overload on the web. They filter and present to customers, small subsets of items that they are most likely to be interested in. Users' interests may change over time, and accurately capturing this dynamics in such systems is important. Sugiyama, Hatano and Yoshikawa proposed to take into account the user's browsing history. Ding and Li were among the first to address this problem, by assigning weights that decrease with the age of the data. Others authors such as Billsus and Pazzani, Li, Yang, Wang and Kitsuregawa proposed to capture long- and short- terms preferences and combine them for personalized search or news access. The Session-based Temporal Graph (STG) is a general model proposed by Xiang et al. to provide temporal recommendations by combining long- and short-term preferences. Later, Yu, Shen and Yang have introduced Topic-STG, which takes into account topics information extracted from data. In this paper, we propose Time Weight Content-based STG that generalizes Topic STG. Experiments show that, using Time-Averaged Hit Ratio as measure, this time weight content-based extension of STG leads to performance increases of 4%, 6% and 9% for CiteUlike, Delicious and Last.fm datasets respectively, in comparison to STG.

1 INTRODUCTION

The amount of information in web sites like Amazon, Netflix and Last.fm is considerable and fast-growing. For users, browsing and searching in such data has become very difficult. To solve this problem, recommender systems filter and present to customers, small subsets of items that they are most likely to be interested in.

Early recommender systems did not take into account temporal information (Herlocker et al., 1999). This is strong limitation because user's profiles and context evolve with time. In this regards Sugiyama et al., (2004) proposed to adapt results according to time-evolving user profiles, based for instance on browsing history. Ding and Li (2005) were among the first to take time explicitly into account by assigning decreasing weights according to their age. Later, some authors proposed to capture both long- and short-term preferences and combine them for recommendations (Billsus and Pazzani, 2000; Li et al., 2007).

Interest in temporal recommender systems increased considerably since the 2009 Netflix grand prize (Koren, 2009). Koren's solution was based on a dataset with items rated by users, whereas in practice, data often contains the history of users in terms of their interactions with items. For instance, Last.fm offers datasets in which each line indicates the fact that user *u* listened to song *i* at time *t*.

In this line of research, Xiang et al., (2010) propose Session-based Temporal Graphs (STG), which model long- and short-term preferences separately. However, they ignore features of items, and so they miss for instance the fact that interest in a piece of music is related to its author. In order to improve this, Yu et al., (2014) extend the STG into Topic-STG for personalized tweet recommendation. They add *topic nodes* to the STG and link tweets to their topics.

These recommender graphs process edges regardless of their age. This fails to capture the fact that in most situation, recent transactions are the most likely to reflect user preferences in the near

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future (Ding and Li, 2005). For example, the clothes that a boy wears have great variability related to his age, thus, the impact of his past dress style on his future dress style decreases with time. To take this into account, we propose here to weight edges according to their age, so that older edges have lower influence. We propose the Time Weight Content-based STG, in which edges are labelled with their last occurrence time, and we use an exponential decay function proposed by Ding and Li (2005) to weight edges accordingly.

The remaining of this paper is organized as follow: Section 2 presents Session-based Temporal Graphs and the two recommendation algorithms, PageRank (Page et al., 1999) and Injected Preference Fusion (IPF) (Xiang et al., 2010) on which our work is built. Section 3 introduces the Time Weight Content-based STG model. Section 4 is devoted to experiments. We discuss related work in Section 5, and we summarize our findings in Section 6.

2 BACKGROUND

We use the notations and definitions proposed by Xiang et al., (2010), together with some additional concepts related to content and time, summarized in Table 1.

2.1 Session-based Temporal Graph

We consider data under the form of a link stream, i.e. a set of triples (t, u, i) representing the fact that user u has selected item i at time t. For each user u (resp. each item i), we define user node v_u (resp. item node v_i). We denote by $\mathbf{T}$ the time span of the dataset and we divide $\mathbf{T}$ into time slices of equal duration. For each of these slices T, we define session node $v_{u,T}$. A session is not defined here as a time slice during which the user interacts with the system. It rather corresponds to a time slice during which a user has a specific behaviour.

A session-based temporal graph $G(U, S, I, E, w)$ is a directed bipartite graph with three types of nodes: U is the set of user nodes, S the set of session nodes and I the set of item nodes. The function w: $E \rightarrow \boldsymbol{R}$ is a non-negative weight function for edges. The set of edges, E, is obtained as follows. For each triplet (t, u, i), let us consider T the time slice to which t belongs. Then, E contains edges (v_u , v_i) and (v_i , v_u), which represent long-term preference between user u and item i; and E contains

Table 1: Notations and definitions.

Symbol	Description
G	bipartite graph STG
CG	bipartite graph Content-based STG
TG	bipartite graph Time weight Content-based STG
E	edge set in any graph
V	set of all nodes in any graph
U, I, S, C	user node set, item node set, session node set, content node set
v_u , v_i , $v_{u,T}$, v_c	user node, item node, session node, content node
w	weight function defined on STG edges
w_C	weight function defined on Content-based STG edges
w_T	time weight function defined on Time weight Content-based STG edges
$\psi(v_k , v_{k+1})$	propagation function of IPF from v_k to v_{k+1}
$out\,(v)$	out node set of the node v
ρ	parameter to control the preference propagation
β	dose of long-term preference injected to user node
η	parameter to adjust the edge weight from item nodes to user/session nodes
η_c	parameter to control the influence of content features in the preference propagation
τ_0	parameter used to compute the time weight function
α	damping factor for PageRank personalization

($v_{u,T}$, v_i) and (v_i , $v_{u,T}$), which represent short-term preferences.

The weight function is defined as:

$$w(v, v') = \begin{cases} 1 & v \in U \cup S, v' \in I \\ \eta_u & v \in I, v' \in U \\ \eta_s & v \in I, v' \in S \end{cases} \quad (1)$$

In (1), η_u models the influence of long-term preferences and η_s models the influence of short-term preferences. To simplify the model, we can use $\eta = \eta_u / \eta_s$ for η_u and 1 for η_s

Fig. 1 is an example of STG with 3 user nodes, 5 session nodes, 7 item nodes and 2 time slices. It shows that user u_1 has selected items i_1, i_2, user u_2 has selected items i_3, i_4 and user u_3 has selected item i_5 during the first time slice T_1. During the second time slice T_2, user u_1 has selected i_3 and user u_3 has selected i_6 and i_7.

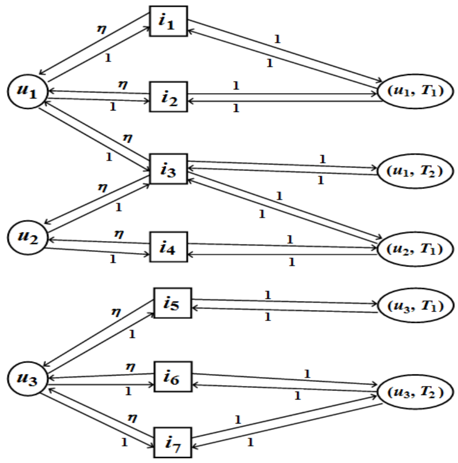

Figure 1: Example of STG.

2.2 Temporal Personalized Random Walk

The Temporal Personalized Random Walk (TPRW) (Xiang et al., 2010) is a personalization of the PageRank algorithm defined by Page et al. (Page et al., 1999) for nodes ranking in graphs. It was defined to tackle temporal recommendation using the idea of Haveliwala (Haveliwala, 2002). It corresponds to the following formula:

$$PR = \alpha \cdot M \cdot PR + (1 - \alpha) \cdot d \qquad (2)$$

where α is the damping factor, M is a transition matrix and vector d is a user-specific personalized vector indicating which nodes the random walker will jump to after a restart.

When making recommendations for user u, vector d favors user node v_u and the most recent session node $v_{u,T}$ as follows:

$$d(v) = \begin{cases} \beta & v = v_u \\ 1 - \beta & v = v_{u,T} \\ 0 & otherwise \end{cases} \qquad (3)$$

In other words, long-term preferences are injected to user node v_u and short-term preferences are injected to session node $v_{u,T}$ through vector d.

When we implement the PageRank with iterative power law method, we stop when the difference of two consecutives rank vectors is of norm less than or equal to a threshold ε.

2.3 Injected Preference Fusion

The IPF algorithm is an extension of the random walk with injection of preferences and customization of preference propagation. To recommend items to a user u, the algorithm proceeds in 3 steps:

- Injection of long-term preferences β on the user node v_u and injection of short-term preferences ($1 - \beta$) on the most recent session node $v_{u,T}$ of user u.
- Propagation of preferences by random walk of length 3 on the graph according to the formula.

$$\psi(v_k, v_{k+1}) = \left(\frac{w(v_k, v_{k+1})}{\sum_{v' \epsilon\, out(v_k)} w(v_k, v')}\right)^{\rho} \qquad (4)$$

- where $out(v_k)$ denotes the set of out-neighbors of node v_k, ρ is a parameter used to tune the propagation process, $w(v_k, v_{k+1})$ is the weight of arc (v_k, v_{k+1}) and $\psi(v_k, v_{k+1})$ is the proportion of preference of v_k that is propagated to v_{k+1}.
- Recommendation of Top-N items that have received the greatest preference values and that user u has not yet selected.

The IPF random walk length is limited to 3 following experimental result (Xiang, et al., 2010).

3 TIME WEIGHT CONTENT-BASED EXTENSIONS OF STG

In this section, we first illustrate how to construct Content-based STG (CSTG) which is similar to Topic-STG (Yu et al., 2014). We end by showing how to construct Time Weight Content-based STG (TCSTG).

3.1 Content-based Session-based Temporal Graph

The basic STG model neglects item properties which can contain significant information for the prediction of user's behaviour. This motivated Phuong et al., (2008) to add to the user-item bipartite graph, new nodes corresponding to content. The same idea is applied here to obtain Content-based STG.

To construct the Content-based STG, we need to have item properties in our data, so we don't use a set of triples like in the construction of STG. We rather use a set of quadruples (t, u, i, c) where t, u and i have the same meaning as in STG, and c is a content feature of i.

Content-based STG $CG(U, S, I, C, E, w_C)$ is a directed graph obtained from the STG $G(U, S, I, E, w)$ by adding for any link (t, u, i, c), the six additional arcs (v_u, v_c), (v_c, v_u), $(v_{u,T}, v_c)$, $(v_c, v_{u,T})$,

(v_i , v_c) and (v_c , v_i). With respective weights 1, η, 1, 1, η_c , η_c as illustrated in Fig. 2.

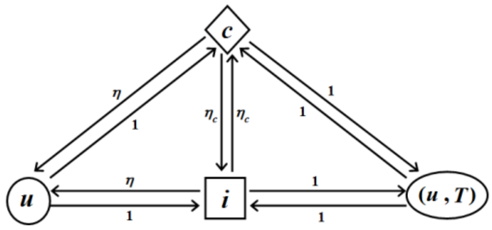

Figure 2: Edge weights in content-based STG.

3.2 Time Weight Content-based Session-based Temporal Graph

The Content-based STG neglects the ages of edges when assigning weights. So, it cannot capture the evolution of users' interest which we assume to be sensitive to time as suggested by Ding and Li (2005). The recommendation model presented here assigns a greater weight to recent edges and lower weight to older edges. More precisely, the weight of the arc (v, v') is defined by:

$$w_T(v, v') = f(t) \cdot w(v, v') \quad (5)$$

where w(v, v') is the weight in the graph without time weight, t is the most recent time at which edge (v, v') appears and f(t) is a time-dependent decay function as in (Ding and Li, 2005). Here we take

$$f(t) = e^{-\lambda \cdot (t_r - t)} \quad (6)$$

where λ is the decay rate and (t_r – t) is the difference in second between time t_r at which we are making recommendations and t.

The parameter λ can also be defined as $\lambda = 1/\tau_0$ where τ_0 is the delay after which the weight of an edge reduces by 1/2. τ_0 is also called half life parameter.

4 EXPERIMENTS

We have conducted a set of experiments to examine the performance of Time weight Content-based STG. For each model, we consider various values of parameters and we retain the best performance. We also implemented the classic bipartite user-item graph (BIP) to show the effects of taking into account long- and short-term preferences in graph models.

The experiment environment is as follow: the executions of our programs are done using a computer with 64GB of RAM and 16 processors Intel of 2.93GHz and 4MB of cache. For implementation, we have used the Python 2.7 language and the Networkx 1.11 module for graph manipulation. Note that we have changed the Networkx *PageRank* in order to stop when convergence is not reached after 100 iterations. We used SQLite 3 as DBMS and Matplotlib 1.4.0 to produce graphics.

4.1 Data Description

Following the example of Xiang et al, our goal is to make recommendations based on implicit data from various real world domains. To this effect, we first perform experiments on the social bookmarking datasets CiteUlike and Delicious (Cantador et al., 2011) which were used in (Xiang et al., 2010). This provides a good basis for the evaluation of the improvement obtained when temporal aspects are taken into account. We also use data from Lastfm (Celma, 2010), a web site where users can listen to music because in this domain the fashion effect plays an important role with the consequence that, the impact of past tastes on the future ones decreases with time.

We model our data as link streams {(t, u, i, c)}, where any quadruple has different interpretation depending on domains. In the case of CiteUlike and Delicious, each quadruplet means that user u has bookmarked page i at time t with tag c. And for the Last.fm data, this means that user u has listened to song i at time t and c is the author of i.

Before modeling our data as link streams, we performed a filtering by ignoring items and users that did not appear a number of times higher than a given threshold σ. Table 2 provides details on our data: date of the first link, date of the last link, total duration of link streams, threshold used, number of users, number of items, number of content features and number of links.

Table 2: Data statistics.

	Start date	End date	Duration	σ
CiteUlike	2010-01-01	2010-07-02	183 days	10
Delicious	2010-05-11	2010-11-09	183 days	7
Last.fm	2005-02-14	2005-08-16	183 days	8
	Users	**Items**	**Content**	**Links**
CiteUlike	1318	424	4216	16885
Delicious	894	298	2789	13825
Last.fm	135	1054	225	41604

4.2 Experiment and Evaluation

The evaluation process is done periodically as in (Li and Tang, 2008) and (Lathia et al., 2009). Before starting experiments, we have to divide the link streams into time windows of a fixed length Δ. We fix Δ to 15 days because humans live at a monthly pace, and the first 15 days are generally characterized by consumption behaviours just after getting salary, that are different from the ones observed during the last 15 days of the month. To simplify the experimentation process, we adopt the same Δ as the length of session when constructing STG. Here after, N denotes the number of time slices.

For each time window W_k, for k=1,..,N-1, we proceed as follows:

- Construct the graphs corresponding to data of W_1, W_2, .. ,W_k.
- Compute the Top-N recommendations for users who have selected at least one "new item" during the time window W_{k+1}.
- Evaluate the algorithm by computing the ratio of users for which at least one of these Top-N items recommends has been selected during W_{k+1}. This proportion is also call Hit Ratio HR_k (Karypis, 2001).

After determining the Hit Ratio for each window, compute the Time Averaged Hit Ratio (TAHR) that is a weighted combination of the N-1 values obtained above for the Hit Ratio. The weight of each Hit Ratio HR_k is the number of corresponding users U_k as in the following equation:

$$TAHR = \frac{\sum_k HR_k \cdot U_k}{\sum_k U_k} \tag{7}$$

Note that, although the convergence may be very slow for some examples, we have noticed that, in most cases, the convergence is achieved after at most 100 iterations.

4.3 Exploration of the Range of the Parameters

Let us see how the parameters are obtained in Table 3. We proceed as in (Xiang et al., 2010). The parameters correspond to the vector [$\tau 0$, β, η, η_c, ρ, α], whose components are numbered 1, 2, 3, 4, 5, 6 from left to right. This vector is initialized to [0, 0.5, 0.5, 0.5, 0.5, 0.5]. Then, we consider the values of $\tau 0$ shown in the second row of Table 3, while maintaining the other parameters at their initial value 0.5. We perform ten experiments and take for $\tau 0$ the value corresponding to the best performance. For instance we obtain for $\tau 0$ the interval [7, 30] for TPRW-TCSTG in CiteUlike dataset as shown in Table 4. Given this optimal value for $\tau 0$ we then give to β the eleven successive values shown in the third row of Table 3, while maintaining the other parameters at their initial value. We obtain for β the interval [0.4, 1] for TPRW-TCSTG in CiteUlike dataset as shown in Table 4. This process is repeated for the remaining parameters.

Figure 3 shows all the variations of Time-Averaged Hit Ratio with parameter values in the case of CiteUlike. The complete set of parameters explored is shown in Table 3 and the best values obtained with this procedure are shown in Table 4.

Table 3: Parameters values.

Parameters	**Initial value**	**Set of values**
$\tau 0$ (in days)	0	0, 1, 7, 15, 30, 45, 60, 90, 180, 365
β	0.5	0.1 × i for i = 0..10
η	0.5	0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1, 1.5, 3, 5, 10, 15, 20, 30, 50, 100
η_c	0.5	0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1, 1.5, 3, 5, 10, 15, 20, 30, 50, 100
ρ	0.5	0.1 × i for i = 0..10
α	0.5	0.1 × i for i = 0..10

4.4 Accuracy Comparison

The performances of PageRank and IPF applied to STG, Time-weight content-based STG, Content-based STG and classical bipartite graph, for the three datasets are presented in Table 5. It can be seen that PageRank applied to the Time weight content-based STG gives the best results, followed by Content-based STG. Moreover, STG is always better than the classical bipartite graph, which confirms the relevance of STG.

Moreover, for PageRank applied to the Time weight content-based STG, the optimal value of the half life parameter $\tau 0$, is less than one month for social bookmarking dataset, but is greater than one month for music dataset. This may be due to the fact that the impact of web pages that someone consulted in the past on those that he is likely to consult in the future decreases very quickly with time. On the contrary, tastes are more stable for music and the impact of a past music does not decrease very quickly.

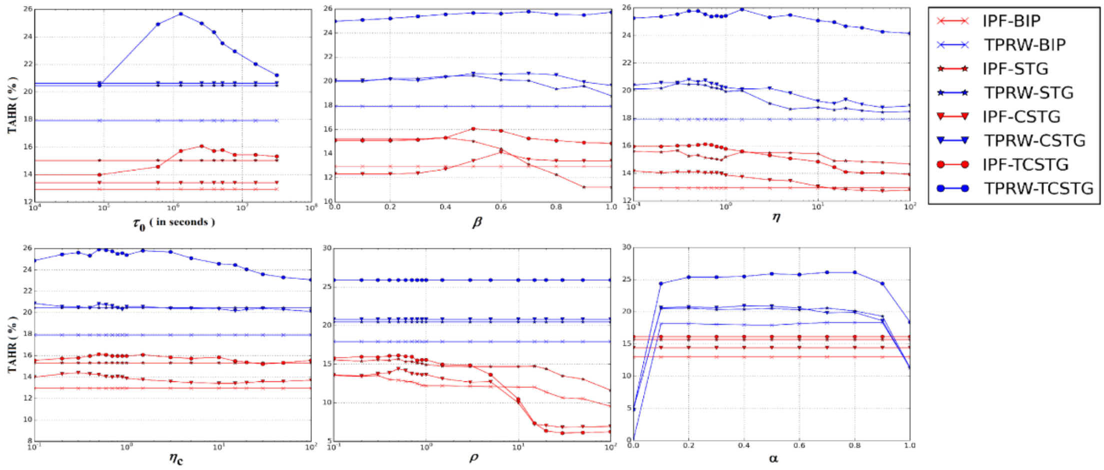

Figure 3: Variation of Time Averaged Hit Ratio with parameter values in the case of CiteUlike.

Table 4: Best parameter values.

CiteUlike	τ_0	β	η	η_c	ρ	α
IPF-BIP	-	-	-	-	0.1-0.3	-
IPF-STG	-	0.0-0.5	0.1-0.3	-	0.1-0.7	-
IPF-CSTG	-	0.5-1	0.0-0.9	0.2-0.5	0.5-0.6	-
IPF-TCSTG	15-60	0.5-0.6	0.1-0.9	0.4-1.5	0.1-1	-
TPRW-BIP	-	-	-	-	-	0.1-0.9
TPRW-STG	-	0.0-0.7	0.3-0.6	-	-	0.1-0.7
TPRW-CSTG	-	0.5-0.8	0.3-0.6	0.1-0.7	-	0.1-0.6
TPRW-TCSTG	7-30	0.4-1	0.3-1.5	0.5-3	-	0.5-0.8

Delicious	τ_0	β	η	η_c	ρ	α
IPF-BIP	-	-	-	-	0.1-10	-
IPF-STG	-	0.0-0.4	0-0.1	-	0.1-0.6	-
IPF-CSTG	-	0.5	15-50	0.3-0.9	0.4-1.5	-
IPF-TCSTG	1-7	0.5-0.6	0.5-0.8	50-100	0.5-1.5	-
TPRW-BIP	-	-	-	-	-	0.1-0.9
TPRW-STG	-	0.0-0.4	0.1-0.2	-	-	0.2-0.5
TPRW-CSTG	-	0.0-0.6	15-100	0.2-0.8	-	0.5-0.7
TPRW-TCSTG	7	0-1	0.5-0.8	0-0.1	-	0.1-04

Last.fm	τ_0	β	η	η_c	ρ	α
IPF-BIP	-	-	-	-	0.1-0.8	-
IPF-STG	-	0.5-1	0.9-1.5	-	1.5-10	-
IPF-CSTG	-	0-0.4	0-0.3	30-100	0.4-0.6	-
IPF-TCSTG	1-15	0-0.4	0.1-0.3	1-100	10-50	-
TPRW-BIP	-	-	-	-	-	0.1-0.5
TPRW-STG	-	0.5-0.7	0.1-1.5	-	-	0.2-0.5
TPRW-CSTG	-	0.2-0.4	0.2-0.5	5-30	-	0.4-0.6
TPRW-TCSTG	30-90	0.5-0.7	0.4-0.6	1-5	-	0.4-0.7

We also think that PageRank has better performance because in this algorithm the propagation process is not limited to the proximity of the source node as in IPF. Indeed PageRank also favours the recommendation of the most popular items of the graph because, even when they are far from the source node, they can be reached and then have a great influence thanks to their high degree.

Table 5: Performances for the best parameters.

	CiteUlike	Delicious	Last.fm
	TAHR (%)	**TAHR (%)**	**TAHR (%)**
IPF-BIP	13.5	7.3	16.3
IPF-STG	15.7	8.6	18.2
IPF-CSTG	14.4	6.4	28.9
IPF-TCSTG	16.1	9.7	26.6
TPRW-BIP	18.3	8.8	27.9
TPRW-STG	20.6	9.2	30.2
TPRW-CSTG	20.9	10.7	37.7
TPRW-TCSTG	**26.1**	**13.2**	**38.9**

5 RELATED WORK

In this section, we present some work on time aware recommender systems followed by recommender systems that use item properties. Finally, we present some graph-based recommender systems.

5.1 Time Aware Recommender Systems

Ding et al. (Ding and Li, 2005) propose the use of an exponential decay function to assign greater weights to latest ratings when computing similarities in collaborative filtering. Subsequently, Liu et al., (2010) have proposed an incremental collaborative filtering where one decay function is used to compute similarities and another one is used for prediction. Recently, Karahodža et al., (2015) assumed that the importance of interest granted to an item decreases in a similar manner for similar users.

Some recommender systems are based on the assumption that importance of information is ephemeral. Thus, Lathia et al., (2009) set a time window size, then, any information is used during one time slice and ignored at the next time window. Such recommender systems only capture short-term preferences.

Some studies are not based only on short-term preferences but also consider that importance of some information persists over time (Li et al., 2007). The STG model (Xiang et al., 2010) extends this work but ignores item properties.

5.2 Content-based Recommender Systems

The content-based recommender systems seek to recommend similar items to the one the user already like. As Lops et al. (Lops et al., 2011) argue, the basic idea is to match features associated to users' preferences and items so as to recommend new items that address their needs. This approach is already used in various domains such as books recommendation on Amazon website based on their description (Mooney and Roy, 2000), and web pages recommendation (Pazzani et al., 1996).

Although content-based recommender systems can propose items that have not already been purchased in the past, it is also useful to use user similarities by combining this approach with collaborative filtering techniques. Indeed, Balabanovic and Shoham (1997) and Basu et al., (1998) show that the combination of collaborative filtering and content-based filtering may result in a recommender system that eliminates the weaknesses of both approaches. In this paper, we have used a graph model to realize this combination.

5.3 Graph based Recommender Systems

The simplest graph-based recommender systems only use user-item links. A bidirectional edge is created between a user node and an item node if the user has purchased the concerned item. Finally, an item is recommended to a user if the user has not yet purchased that item and if there is a path from the user to that item. The most used recommender algorithms on the graphs are based on the random walk (Baluja et al., 2008), like PageRank and IPF which are used in this paper.

The use of graph paths to recommend new items can be seen as collaborative filtering where similaritys defined through node distance. However, such recommender graphs do not take into consideration item properties. To remedy this limitation, Phuong et al., (2008) have constructed a recommender graph in which they have added a third node type: the type “content”. The obtained recommender system is actually a combined collaborative filtering and content-based filtering. The associated graph ignores the temporal aspect of data and therefore cannot accurately capture short- and long-term preferences. Yu et al., (2014) propose the Topic-STG which combines those two preferences and takes into account topics related to tweets. However, those models handle edges regardless of their age. This is not in accordance with concept drift. This is why we propose a new extension of STG where edge weights are decreased using a time decay function as in (Li and Tang, 2008).

6 CONCLUSIONS

This paper proposes time weight content-based extensions of the temporal graph model introduced by Xiang et al., As in Topic-STG introduced by Yu, Shen and Yang, we represent content by nodes, but we penalize older interactions. Experiments show that, using Time-Averaged Hit Ratio as measure, this time weight content-based extension of STG leads to performance increases of 4%, 6% and 9% for CiteUlike, Delicious and Last.fm datasets respectively, in comparison to STG. This gives evidence of the fact that the age of interactions is a relevant feature for recommender systems.

More experiments using datasets from various domains are needed in order to adjust the length of time windows and other parameters.

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