Exploring current viewing context for TV contents recommendation

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***Abstract*—Due to the diversity of alternative programs to watch and the change of viewers' contexts, real-time prediction of viewers' preferences in certain circumstances becomes increasingly hard. However, most existing TV recommender systems used only current time and location in a heuristic way and ignore other contextual information on which viewers' preferences may depend. This paper proposes a probabilistic approach that incorporates contextual information in order to predict the relevance of TV contents. We consider several viewer's current context elements and integrate them into a probabilistic model. We conduct a comprehensive effectiveness evaluation on a real dataset crawled from Pinhole platform. Experimental results demonstrate that our model outperforms the other context-aware models.**

Keywords: Context-based, TV-Recommender systems, Probabilistic model

I. Introduction

Recently, context-aware recommender systems play a critical role in different domains such as events, locations and music recommendation. Generally, their effectiveness is due to the integration of additional information that define the specific situation under which recommendations are made. For example, a user might prefer to watch world news (e.g. CNN or BBC) in the morning with colleagues and movies recommended by friends on weekends.

Several works [9], [1], [18], [2] have recognized that the use of contextual information can greatly improve the recommendation process.

An effective context-aware system must take into account several types of contextual information. For instance, the current weather and the week day of a user might have an impact on the relevance of a TV content.

On the other hand, the rapid growth of channels' number has increased the alternative programs to watch and multiplied the choices of consumers for TV content consumption. Therefore, due to viewers' contexts change according to the diversification of televisual contents, viewers are having hard times to decide which program to watch among thousands of choices.

However, most of the existing personalized TV systems [6], [14], [22], [10] consider only the current time information. Other viewing contexts such as location, weather, week day and the occasion are ignored in TV content recommendation process.

Likewise, real-time prediction of viewers' preferences in certain circumstances becomes increasingly hard for TV producers.

In our work, we define the *viewing context* as a specific set of attributes of the viewer environment that could influence her preferences.

Furthermore, most of the proposed TV recommender systems [17], [22], [14], [4], [6], [8], [5] draw on collaborative-based filtering (CF) [20], [11] and content-based [15] methods. Unfortunately, they have few consideration about solving recommender problems (e.g. no TV programs seen by a new user known as "cold start problem", and not enough co-rated TV programs with other users with similar preference known as "sparsity problem").

In addition, other approaches [13], [9] incorporate contextual information in a heuristic way. They commonly used matrix factorization techniques. As proved by [3], [12], [16], the major drawback of matrix factorization techniques is the non-convexity scheme. Therefore, there is in general no algorithm that guarantees the computing of the desired factorization for user-item ratings. In addition, matrix factorization techniques fail to consider several factors to jointly integrate several context elements in one matrix factorization model.

In this paper, we propose a probabilistic model that can dynamically adapt users' preferences to changes in viewing context. We jointly leverage current contextual information in order to improve TV content recommendation.

In particular, the probabilistic model aims to predict the relevance of TV contents for a user based on his/her current viewing context.

We conduct a comprehensive effectiveness evaluation on a real dataset crawled from Pinhole platform. We test the ability of our model to solve data sparsity and viewer cold start problems. Experimental results validate the effectiveness of our model comparing to time-aware models.

The remainder of this paper is organized as follows. Section 2 summarizes the related work on TV recommender systems and context-based models. Section 3 introduces our model which seamlessly captures contextual information. Section 4

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reports the experimental results and findings. Finally, Section 5 concludes the paper and points out the future direction.

II. Related Work

In this section, we review related works, including TV content recommendation systems and context-aware methods.

A. TV content recommendation

Several Social TV services and platforms were implemented in the last few years (e.g. Netflix, GetGlue, GoogleTV). This allows the TV experience to move beyond the traditional confines of entertainment into a more holistic media. Obviously, according to "Netflix Challenges"[1], Netflix algorithms draw on the item-based collaborative filtering method and Matrix Factorization method to predict users′ preferences.

Likewise, many approaches have been proposed for TV content recommendation [17], [22], [14], [4], [6], [5].

Pyo et al. [17] defined an automatic recommendation scheme of TV program contents in sequence using sequential pattern mining based only on user's watching history. They proposed a weighted normalized and modified retrieval rank metric for similar user grouping taking into account the watching order and the weights of preferred TV program contents. Then, for each group of users, they defined a sequential pattern (a sequence of TV programs to recommend) which is constructed based on features such as the occurrence of frequently watched TV programs from the targeted users.

Antonelli et al. [4] proposed a content-based recommender approach using the textual descriptors associated to TV contents extracted from newspaper articles. They used a matrix factorization technique to associate textual descriptors to TV contents.

Martinez et al. [6] introduced a personalized TV program recommendation system. They proposed a hybrid approach that combines content-filtering techniques with collaborative filtering and provides advantages. They used vector space model to generate content-based recommendations. They used SVD (Singular Value Decomposition) to reduce the dimension of the active item's neighborhood.

Additionally, different architectures of personalized videos recommendation systems proposed in the literature were outlined by the survey presented by Asabere [5].

Unfortunately, most works described above draw on collaborative-filtering (CF) based [20], [11] and content-based [15] methods. They have few consideration about solving recommender problems (e.g. users' manipulations on TV shows ratings known as "shilling problem" and not enough co-rated TV programs with other users with similar preference as "sparsity problem"). In addition, they did not exploit current viewers' contexts (e.g. actual weather) to predict their preferences.

[1] http://www.netflixprize.com/

B. Context-awareness

Viewers' preferences on TV content dynamically change according to circumstances and situations which the viewer faced. The importance of integrating contextual information into recommendation process has been recognized by several works [9], [1], [18] in various recommendation applications such as events, locations and music recommendation.

In the Context-aware Movie Recommendation CAMRa Challenge [19], participants exploited several time features (e.g. temporal relevance, the date) derived from the available timestamps based on matrix factorization techniques.

The intuition behind matrix factorization techniques is to learn latent features that determine how user rates an item. The existing ratings can be represented in a matrix R of size $|U| \times |V|$, where U is the set of users and V is the set of items. The aim is to discover K latent features u_i^T and v_j which correspond to the i-th column and the u-th column of U and V, respectively. Then , the task is to find two matrices P of size $|U| \times K$ and Q of size $|V| \times K$ such that their product approximates R:

$$R \approx P \times Q^T = \hat{R} \qquad (1)$$

Based on this parametrization, the predicted rating is computed as follows:

$$\hat{r}_{ui} = u_i^T \times v_j \qquad (2)$$

The parameters u_i^T and v_j are learnt based on a certain loss function in order to minimize iteratively the difference between their product and the matrix R.

Adomavicius et al. [18] surveyed contextual modeling methods and divided them into two categories: Heuristic-based approaches and Model-based approaches. Furthermore, they proved that the proposed context-aware recommender approaches can be significantly more complex because contextual information needs to be elicited from the user and due to the variety of contextual information types.

Gantner et al. [9] used an approach from tag recommendation, Pairwise Interaction Tensor Factorization (PITF) where weeks were used to form user-movie-weeks tensors. They integrated time factors into the similarity calculation of neighborhood based methods for time-aware CF.

However, few works [22], [8], [14], [13] have considered several contextual information in TV content recommendation applications. This is partly due to the fact that it is more difficult to capture contextual information by TV recommender systems.

A time-dependent profile technique was proposed by Oh et al. [14]. The construction of this profile is based on splitting each Watch Log into time slots and generating a time-dependent profile for each time slot. Therefore, when a recommendation is issued, the system finds the corresponding profile based on the time stamp of the request.

Unfortunately, this method causes a loss generality problem because some profiles will be totally generated by a specific

Ref.	Content-based	Collaborative-filtering	Matrix factorization	Integrating temporal factor	Integrating other context elements	Sparsity problem	Cold start problem
[13], [9], [6]	−	+	+	+	−	−	−
[22], [14]	+	−	−	+	−	−	−
[17]	−	+	−	+	−	−	−
[6]	+	+	+	−	−	−	−
[8]	−	+	−	−	−	−	−
Proposed Model	−	+	−	+	+	+	+

TABLE I
COMPARISON OF PROPOSED MODEL AGAINST RELATED WORK APPROACHES.

program, and users are likely to watch the same programs. In consequence, the dependency for a specific program and time may incur the overspecialization issue.

In [22], the user model is built by incorporating the time context and other features (i.e. the genre, the sub-genre and the viewing history). A smoothing function is used in order to aggregate user preferences in each time slot with his preferences in neighboring time slots.

Chang et al. [8] presented a user profile analysis model based on demographic information.

Therefore, most existing context-aware approaches for TV content recommender systems used only current time information and ignore other important contextual information on which viewers' preferences undoubtedly depend. Temporal-based models are challenging because the ratings' matrix is sparse and the use of specific temporal feature may alleviate the sparsity problem.

Our approach is different from the other approaches, as we are interested in capturing and adapting several context elements changes to viewers' preferences in a generic way, and considering sparsity and cold start problems. The comparison of the proposed model against related work approaches is described in Table I.

In our work, we define *current viewing* context as the set of circumstances related to the actual environment of the viewer while watching a TV content that may influence his/her preferences. Additional contextual information could be integrated in a generic way, such as the weather, the occasion and the company of other people in order to improve recommendation accuracy.

Unfortunately, despite the fact that matrix factorization techniques is commonly used by most works [13], [9], they are considered as the most complex techniques. This is due to their major drawback related to the non-convexity scheme.

As proved by [3], [12], [16], there is in general no algorithm that is guaranteed to compute the desired factorization. In addition, matrix factorization techniques fail to consider the structure in the data such as the nature of relationships between users.

III. PROPOSED APPROACH

We aim to exploit contextual information in a generic way in order to mine personal preferences of viewers and to incorporate the viewing context for TV content relevance prediction.

We propose a probabilistic model that quantitatively captures contextual information in a generic way in order to mine viewers' preferences in certain contexts.

We consider a graph $G = (N, L)$ where N represents nodes (Viewers and Videos) and L represents the set of links between nodes.

We refer to the set of viewers as U and to the set of videos as V. $V(u)$ represents the set of videos viewed by user u and $U(v)$ represents the set of users which have viewed video v.

L may link a viewer u and a video v. L represents the context in which user u has viewed video v.

Let C be the set of all viewing contexts, $c_{uv} \in C$ is the viewing context of u in which he viewed video v. A viewing context c_{uv} is represented as a set of properties $c_{uv}\{c_{1uv}, \ldots, c_{muv}\}$ (i.e. *time slot*, *the location*, *the week day*, *the weather* and *the occasion*).

For example, Jessica regularly watched romantic movies on weekend night. However, this weekend she woke up early and decided to watch TV.

Intuitively, Jessica's viewing rating is decided by both her preferences and her current context.

Her current context is $c_{Jessica}$ = {**location=** London Soho, **time slot=** 08-09, **weekday=** Saturday, **weather=** 9°, **occasion=** weekend morning}.

Jessica's interests will be reflected from other users' preferences in similar contexts.

The goal of our probabilistic approach is to estimate the relevance of the target video v for the target user u given his current context $c_u\{c_{1u}, \ldots, c_{mu}\}$. We aim to predict $Pr(r_{uv} = k|c = c_u)$ which is the conditional probability that the target viewer u's rating on video v is equal to value k, given the current context c_u of viewer u. c_u represents the current context of viewer u. Then, videos with high probabilities will be recommended to viewer u.

$Pr(r_{uv} = k|c = c_u\{c_{1u}, \ldots, c_{mu}\})$ is the conditional probability that the target user u, within a viewing context $c \in C$ similar to his current context c_u, will rate v with value k. This probability represents viewer u's preferences given his current context c_u.

We consider the dynamic change of viewer preferences according to his current context considering the context-based model. We aim to estimate the relevance of video v for user u given his current context c_u.

$Pr(r_{uv} = k|c = c_u)$ estimates the conditional probability that the rating r_{uv} given by user u on video v is equal to value k given viewer u's current viewing context c_u. This probability can be estimated as the relevance of video v for viewers having approximately the same viewing context than u.

Based on Bayes rule, $Pr(r_{uv} = k|c = c_u)$ could be factorized as follows:

$$\begin{aligned} & Pr(r_{uv} = k|c = c_u\{c_{1u}, \ldots, c_{mu}\}) \\ = & \frac{Pr(c = c_u\{c_{1u}, \ldots, c_{mu}\}|r_v = k) \times Pr(r_v = k)}{Pr(c = c_u\{c_{1u}, \ldots, c_{mu}\})} \end{aligned} \tag{3}$$

Because this probability depends on the context elements' values rather than the user u, we drop the subscript u in r_{uv} for simplification.

We also assume that context properties are all independent from each others. Then, $Pr(r_{uv} = k|c_u\{c_{1u}, \ldots, c_{mu}\})$ can be written as follows:

$$\begin{aligned} & Pr(r_{uv} = k|c = c_u\{c_{1u}, \ldots, c_{mu}\}) \\ = & \prod_{i=1}^{m} \frac{Pr(c_i = c_{iu}|r_v = k) \times Pr(r_v = k)}{Pr(c_i = c_{iu})} \end{aligned} \tag{4}$$

where c_i is the element i of the current context.

We assume that $Pr(c_i = c_{iu})$ is uniform. Thus the probability can be estimated as follows:

$$\begin{aligned} & Pr(r_{uv} = k|c = c_u\{c_{1u}, \ldots, c_{mu}\}) \\ \propto & \prod_{i=1}^{m} Pr(c_i = c_{iu}|r_v = k) \times Pr(r_v = k) \end{aligned} \tag{5}$$

In order to avoid strong probabilities (0 or 1), we used Laplace smoothing technique [7]. $Pr(r_{uv} = k|c = c_u) = 0$ if there are no views' rating equal to k for all context elements and $Pr(r_{uv} = k|c = c_u) = 1$ if all ratings are equal to k in all contexts. Laplace smoothing technique is an effective technique to solve strong probabilities problem particularly for small size of training samples.

$$\prod_{i=1}^{m} Pr(c_i = c_{iu}|r_v = k) = \prod_{i=1}^{m} \frac{|r_v = k, c = c_{iu}| + 1}{|r_v = k| + nc_i} \tag{6}$$

where $|r_v = k, c_i = c_{iu}|$ represents the number of ratings equal k on video v and where u's viewing context item is c_{iu}, $|r_v = k|$ is the number of views of v where rating equals to k regardless the viewing context and nc_i is the number of possible values for each context element.

We aim to estimate $Pr(r_v = k)$ which is the probability of having a rating equal to k for video v. We also used Laplace smoothing technique as shown in Equation 7.

$$Pr(r_v = k) = \frac{|r_v = k| + 1}{|r_v| + nr} \tag{7}$$

where $|r_v = k|$ is the number of ratings on video v equal to value k, $|r_v|$ is the number of ratings on v and nr is the number of possible rating values.

IV. Experiments

In this section, we conduct an effectiveness evaluation using real data collected from Pinhole social TV platform. This dataset includes viewer-video access history and viewers' friendship networks.

In addition, we collect contextual information for each viewer-video access history captured by the platform system. The platform system captures and records the last contextual information that the viewer faced while watching such a video.

In our evaluation, we adopt *Time-aware Collaborative Filtering (TCF)* and *Time-Dependent Profile (TDP)* as baseline models.

Besides, we propose to study the effectiveness of each element of the viewing context. We considered the location, time slot, weekday, weather and occasion in our context-based model.

We conduct experiments in order to test the ability of our model to solve data sparsity and cold start problems, as described in [21].

A. Data Description

In order to conduct our experiments, we used a subset of Pinhole[2] data which is a Tunisian social TV platform created in 2012. Our dataset includes 16,000 users, 81,000 TV shows and 721,121,391 views.

The statistics of these data are displayed in Table II.

Statistics	Quantity
Number of users	16,000
Number of TV shows	81,000
Number of views	721,121,391

TABLE II
STATISTICS OF USED DATASET

Each edge that links nodes u and v represents viewing context within which the user u watched the show v. Each viewing context represents a set of properties.

We considered the following context elements: the location, the time slot, the weekday, the weather and the occasion. These properties are captured by the context detector of Pinhole system. The weekday and the occasion are captured from the viewer schedule (e.g. anniversary, workout, party, meeting). The weather is captured according to the detected location and the time slot.

However, we do not rate explicitly TV programs. We estimate user rating r_{uv} according to the time spent watching a TV show:

$$\begin{aligned} & r_{uv} \\ = & \frac{Number\ of\ minutes\ viewer\ u\ watched\ video\ v}{Number\ of\ minutes\ in\ video\ v} \end{aligned} \tag{8}$$

[2]www.pinhole.tn

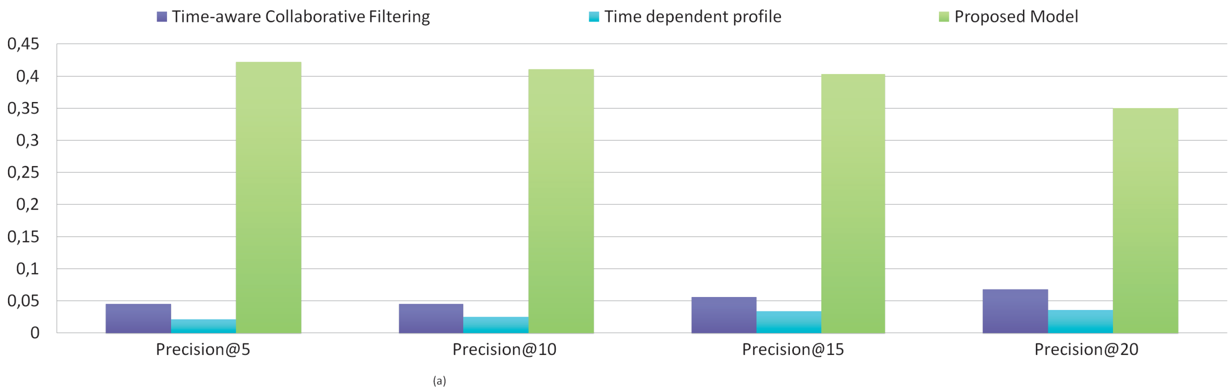

Fig. 1. Comparison with baseline models on Precision

B. Baseline Models

We compare the proposed model with the following techniques:

a) Time-aware Collaborative Filtering (TCF) [13]: The authors implemented a time-aware collaborative model for movie recommendation.

Based on the assumption that recent ratings are more important than historical ones, they incorporated temporal relevance using a matrix factorization technique.

The temporal relevance $f_{ui}(t)$ measures the relevance of each observed rating r_{ui} of user u on item i in order to make recommendation to viewer u at time t, as defined in Equation 9.

$$f_{ui}^{\beta}(t) = e^{-\beta(t-T_{ui})} \tag{9}$$

where β is the parameter controlling the decaying rate.

They used a Singular Value Decomposition (SVD) technique based on the loss function defined in Equation 10.

$$\min_{U,V} \sum_{i=1}^{m}\sum_{u=1}^{n} w_{ui}.(r_{ui} - u_i^T.v_u)^2 + \lambda(||U||_F^2 + ||V||_F^2) \tag{10}$$

Where w_{ui} is calculated as follows:

$$w_{ui} = 1 + f_{ui}^{\beta}(t) \times (w_{max} - 1) \tag{11}$$

w_{max} is a parameter used to control the maximum weight that could be assigned to a rating.

b) Time-Dependent Profile (TDP) [14]: The authors proposed a time-dependent recommendation technique. The construction of the user profile is based on splitting each watch log into time slots and generating a time-dependent profile for each time slot.

Therefore, when a recommendation is issued, the system finds the corresponding profile based on the time stamp of the request.

Then, the similarity between video v and each video v' in the corresponding profile is calculated based on Pearson correlation coefficient between them, as defined in Equation 12.

$$similarity(v, v') = \frac{\sum_{u'\in U}(r_{u'v} - \overline{r_v}) \times (r_{u'v'} - \overline{r_{v'}})}{\sqrt{\sum_{u'\in U}(r_{u'v} - \overline{r_v})^2} * \sqrt{\sum_{u'\in U}(r_{u'v'} - \overline{r_{v'}})^2}} \tag{12}$$

The information about the set IT of videos with a similar rating pattern compared to video v under consideration is the basis for predicting the rating of user u on video v and can be estimated as follows:

$$prediction(u, v) = \frac{\sum_{it\in IT} similarity(v, it) \times r_{u,it}}{\sum_{it\in IT} similarity(v, it)} \tag{13}$$

C. Evaluation setup and metrics

We perform 5-fold cross-validation. In each fold, 80% of videos was randomly selected as the training set and remaining 20% as the testing set. The evaluation focused on two recommendation tasks.

The first one is the video list recommendation task where we evaluate precision. Then, we assess if the recommended videos with high probabilities were really viewed by the target user u. We used Precision of top x $(x = 5, 10, 15, 20)$ recommendations.

The second one is a video rating prediction task in which the accuracy metrics are MAE and $RMSE$ computed respectively in Equation 14 and Equation 15.

$$MAE = \sqrt{\frac{1}{N}\sum_{v\in N} |q_{uv} - p_{uv}|} \tag{14}$$

Context element	Precision@10	Impact
Location	0.251	-0.16
Time Slot	0.28	-0.131
Week day	0.384	-0.027
Weather	0.373	-0.038
Occasion	0.31	-0.101

TABLE III
PRECISION@10 AFTER ELIMINATING EACH CONTEXT ELEMENT AND ITS IMPACT ON PREDICTION PERFORMANCE

Context element	Precision@10	Impact
Location	0.052	-0.359
Time Slot	0.064	-0.347
Week day	0.017	-0.394
Weather	0.03	-0.381
Occasion	0.022	-0.389

TABLE IV
PRECISION@10 AFTER KEEPING ONLY ONE CONTEXT ELEMENT AND ITS IMPACT ON PREDICTION PERFORMANCE

$$RMSE = \sqrt{\frac{1}{N}\sum_{v \in N}(q_{uv} - p_{uv})^2} \tag{15}$$

Where q_{uv} is the real rating of viewer u for video v, p_{uv} is the predicted rating of viewer u for video v and N is the number of recommended videos.

Based on the empirical study of this work, $\mu = 500$ is the best setting.

D. Results

Figure 2 reports Precision, MAE and $RMSE$ of all comparison models discussed above. As shown in Figure 1, the proposed model significantly outperforms all compared approaches in terms of Precision of top 5 to top 20. It outperforms TCF model by more than 40% and outperforms the TDP model by 36%. Figure 2 presents results on accuracy of rating prediction in terms of $RMSE$ and MAE.

From Figure 2, we note that our model also outperforms the prediction accuracy of all baseline models in terms of MAE and $RMSE$. Our model outperforms the prediction accuracy of TCF model by more than 0.15 and outperforms the TDP model by 0.20.

E. Context elements impact

We study the impact of each element of the viewing context. In other words, we evaluate the importance of each context element in prediction performance.

In this study, we realize two experimental tasks.

1) The first one is based on removing only one context element:

We implement 5 instances of our model. In each instance, we removed one context element. Then, we evaluate $Precision@10$ of each model instance.

Table III indicates that all the context elements are essential for the prediction model. The most important ones are location, time slot and occasion. Obviously, if we eliminate the location or the time slot from the model, precision decreases by more than 13%.

However, precision decreases at most by 3% for week day, the weather and the occasion. Therefore, we note that viewers' preferences are more context-sensitive to location and time slot.

In the case of the $RMSE$, the result implies that our recommendation approach, compared to the time-aware models, provides better personalized recommendation to viewers who face with specific contexts.

2) The second task consists in keeping only one context element:

We implement 5 instances of our model. In each instance, we keep only one context element. Then, we evaluate $Precision@10$ for each model instance.

Table IV indicates that all the context elements are complementary for the prediction model. The most important ones are location and time slot. Obviously, if we keep only the location or the time slot from the model, precision decreases by more than 34%.

However, precision decreases at most by 39% for week day, the weather and the occasion. Therefore, we note that viewers' preferences are more context-sensitive to location and time slot.

In the case of the $RMSE$, the result implies that our recommendation approach performs better personalized recommendation to viewers who are faced with specific contexts, compared to the time-aware models.

F. Data sparsity problem

In this study, we aim to evaluate the effectiveness of our model at various levels of data sparsity.

Thus, we randomly divided the viewer/video pairs of our dataset into ten groups.

Then, we randomly selected n sets as testing set and the rest as training set. We measured the MAE and the $RMSE$ for each value of n.

Table V compares the MAE and $RMSE$ of our model when testing sets vary from 10% to 70%.

As it can be expected the general behavior of these approaches is the same. The effectiveness of the other approaches are correlated with the size of the training data.

However, the results show clearly that the MAEs of our model are consistently lower than those of baseline models.

In addition, we observe that matrix factorization techniques are highly affected by data sparsity.

For instance, the MAEs of TCF model increases by 0.17 from 0.61 when the testing set increases from 10% to 70%, whereas the MAEs and $RMSE$s of our model increases at a much slower space.

Temporal-based models are challenging because the ratings' matrix is sparse and the use of specific temporal feature alleviates the sparsity problem.

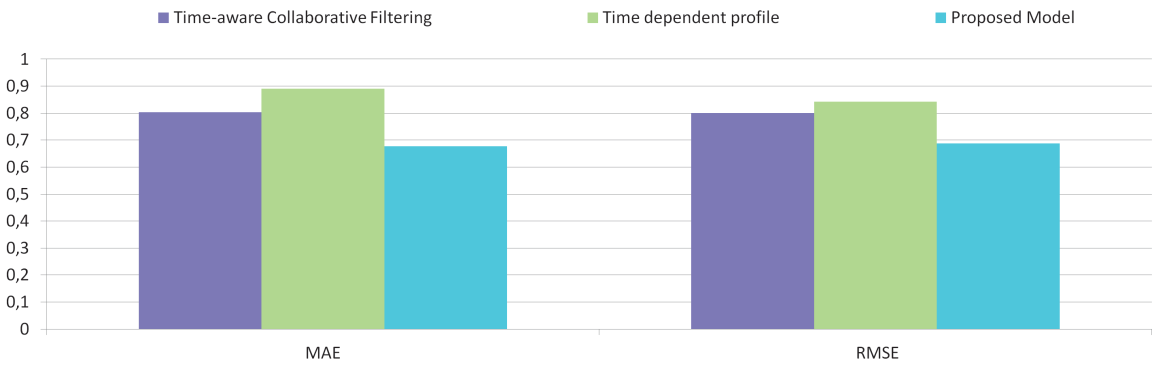

Fig. 2. Comparison with baseline models on MAE and RMSE

		10%	20%	30%	40%	50%	60%	70%
Time-aware Collaborative Filtering (TCF)	MAE	0.792	0.802	0.921	0.93	0.97	0.98	0.98
	RMSE	0.76	0.80	0.83	0.84	0.921	0.98	0.982
Time-Dependent Profile (TDP)	MAE	0.85	0.89	0.93	0.96	0.97	0.97	0.98
	RMSE	0.84	0.842	0.86	0.87	0.871	0.95	0.98
Proposed Model	MAE	0.617	0.623	0.628	0.66	0.71	0.73	0.782
	RMSE	0.62	0.628	0.72	0.73	0.76	0.80	0.815

TABLE V
COMPARISON OF MAEs AND RMSEs OF OUR PROPOSED MODEL AND BASELINE MODELS AT DIFFERENT SIZES OF TESTING SET.

	MAE	RMSE
Time-aware Collaborative Filtering (TCF)	0.803	0.81
Time-Dependent Profile (TDP)	0.89	0.842
Proposed model	0.714	0.738

TABLE VI
ANALYSIS OF COLD START PROBLEM BASED ON MAEs AND RMSEs

G. Cold start problem

Now we conduct experiments to test the ability of our model to solve viewer cold start recommendation problem. The cold start problem occurs when a new user has no seen videos. We compare our model with time-aware and time-dependent models. We simulate the cold start for each user in the dataset. We did not take into account the target viewer ratings in the training set.

However, we considered the actual contextual information of the user. As showed in Table VI, the resulting MAE is 0.71 and $RMSE$ is 0.73. The results show significant improvement compared to the TCF and TDP models in terms of MAE and $RMSE$. This is due to the fact that CF techniques cannot make recommendation to new viewers because they cannot find similar viewers.

Additionally, our model outperforms $SNMF$ model in terms of MAE and $RMSE$ by more than 0.15. This is due to the fact that matrix factorization techniques cannot integrate features other than temporal feature to solve cold start problem.

V. CONCLUSION

In this paper, we propose a probabilistic approach which unifies contextual information into the recommendation process. We exploit several viewing context information. In our experimental studies, the proposed model achieves the best results comparing to Time-aware Collaborative Filtering Model (TCF) and Time-Dependent Profile Model (TDP) in terms of prediction accuracy. In the sparsity and cold start tests, our model returns consistently accurate predictions at different values of data sparsity. The performance of our model can be further improved by integrating social influence between users on the relevance of TV content. The encouraging results open several future directions such as enriching TV shows' profiles based on keywords related to viewers interactions and use other evaluation metrics such as the serendipity and the diversity in order to better evaluate recommendation accuracy.

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