Global Journal of Computer Science and Technology: D
Neural & Artificial Intelligence
Volume 18 Issue 1 Version 1.0 Year 2018
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals
Online ISSN: 0975-4172 & Print ISSN: 0975-4350

An Analysis of Emotion and user Behavior in Context-Aware Travel Recommendation Systems using Pre-Filtering and Tensor Factorization Techniques

By Piumi Ishanka UA & Takashi Yukawa

Nagaoka University of Technology

Abstract- The emotion-based context-aware recommendation systems have been widely adapted by a wide variety of recommendation domains despite the fact only a few studies have been analyzed in tourist destination recommendations. To utilize the concept of user emotion and incorporate it into the recommendation process along with user behavior, we proposed a travel destination recommendation system. Also, we compare and clarify the effectiveness of using emotion and user behavior in the recommendation process by suggesting a framework based on two techniques: filtering and contextual modeling. For the filtering based approach, we used Prefiltering, and for the contextual modeling, we employed Tensor Factorization. Both these approaches performed excellently with the selected contexts in the proposed framework, and the results of the Tensor Factorization approach proved to be highly effective in tourist destination recommendation compared to other Pre-filtering.

Keywords: *context-aware place recommendation, pre- filtering, tensor factorization.*

GJCST-D Classification: *J.4, I.m*

Strictly as per the compliance and regulations of:

An Analysis of Emotion and user Behavior in Context-Aware Travel Recommendation Systems using Pre-Filtering and Tensor Factorization Techniques

Piumi Ishanka UA[α] & Takashi Yukawa[σ]

Abstract- The emotion-based context-aware recommendation systems have been widely adapted by a wide variety of recommendation domains despite the fact only a few studies have been analyzed in tourist destination recommendations. To utilize the concept of user emotion and incorporate it into the recommendation process along with user behavior, we proposed a travel destination recommendation system. Also, we compare and clarify the effectiveness of using emotion and user behavior in the recommendation process by suggesting a framework based on two techniques: filtering and contextual modeling. For the filtering based approach, we used Pre-filtering, and for the contextual modeling, we employed Tensor Factorization. Both these approaches performed excellently with the selected contexts in the proposed framework, and the results of the Tensor Factorization approach proved to be highly effective in tourist destination recommendation compared to other Pre-filtering.

Keywords: context-aware place recommendation, pre-filtering, tensor factorization.

I. Introduction

Currently, information systems are mainly being confronted by the challenge of information overload and alleviative methods are required to cope with and ultimately overcome this problem effectively and efficiently. Recommendation systems act as intelligent agents that provide solutions; the actual recommendation procedure is being stated as "the process of utilizing the opinions of a community of customers to help individuals in that community for more effectively identifying the content of interest from a potentially overwhelming set of choices."[1]. The of context-awareness has been introduced to the recommendation domain to increase the efficiency and usability of information filtering systems while providing solutions to information overload. Context-awareness emerged to acquaint users with the influence of the external environment on his/her appreciation of the items. Recently, however, not only the physical status but also users' psychological conditions are considered in the recommendation process. In the context-aware recommendation domain, many contextual features have been identified as contextual parameters, for instance companion in the movie recommendation domain, time and mood constraints in the music recommendation, and weather, season, travel type, etc., in the travel recommendation domain [2].

Much research has examined the application of context on the effective recommendation solutions in a variety of domains [3], [4], [5], [6]. In our study, we mainly focus the incorporation of emotion and user behavior as contextual parameters and try to compare the feasibility of the selected parameters on one of the challenging domain, travel recommendation compared to classical recommendation domains like movies, music, books, etc. Emotion has been used as a contextual parameter in several studies recently, and a few studies have made an effort to discuss the effectiveness of emotion in the recommendation process [7] with a real-world dataset, for example, LDOS-CoMoDa which is a movie dataset. Recently, recommendation systems have revealed a prodigious tendency to adapt emotion due to its effectiveness in human decision-making processes. These research efforts have been conducted independently and extended to two major research domains, i.e., Recommender systems and Affective computing. In particular, the user behavior actions; rating and tagging emotion were added to our study to analyze the effectiveness in the presence of both parameters together and individually in the proposed travel destination recommendation system. The context-aware dataset on travel recommendation is hard to find compared to traditional recommendation domains. Firstly, we derived our dataset based on user reviews for each destination chosen for the study by employing Semantic Analysis concepts. Secondly, we compared each parameter's effectiveness on travel destination recommendation by using the Pre-filtering technique and Tensor Factorization. Consequently, this study focuses on investigating the context-aware recommendation based on the parameters, user behavior, and emotion. The key objective of this paper is

Author α σ: Department of Information Science and Control Engineering, Graduate School of Engineering, Nagaoka University of Technology, 1603-1, Japan. e-mails: s135063@stn.nagaokaut.ac.jp, yukawa@vos.nagaokaut.ac.jp

Global Journal of Computer Science and Technology (D) Volume XVIII Issue I Version I Year 2018

to propose a framework for the traveler destination recommendation system, exploiting the emotion and user behavior while optimizing each contextual parameter in the recommendation.

a) *Our contribution*

In this paper, we propose two foremost contributions for context-aware travel recommendation. We chose two contextual parameters - emotion and user behavior, and we implement the recommendation engine by using Pre-filtering techniques and then compare the effectiveness of the recommendation systems with the absence of any contextual parameter. Furthermore, we associate how individual contexts perform in the recommendation process by implementing the recommendation system with Tensor Factorization and comparing the results for each parameter. Finally, we compare two approaches, specifically Pre-filtering and Tensor Factorization for each context. We evaluate all the implemented methods with precision, mean average precision, mean average precision with emotion groups, the t-test (to check the difference in average precision and average preference ratings) and overall user satisfaction. The results of the study conclude the feasibility of selected contexts in travel recommendation. The rest of the paper is structured as follows.

The next section provides a brief overview of the related work, i.e., context and context selection, context awareness, the state-of-the-art of travel recommendation systems, contextual pre-filtering and context modeling techniques. Section three discusses an overall structure and implementation process of our proposed travel destination recommendation system. Section four evaluates the performance of the proposed system. The final section documents the concluding remarks on the major themes covered here and directions for further research.

II. Background

a) *Context and context-awareness*

The context has been defined in multiple ways and described as a multifaceted concept in different research domains [8]. Most of the contextual information concerns characteristics of an activity such as location, time and some dynamic features of user profiles, for example users' emotional state [9]. Hence, information e.g. location, time, social companion, and mood, etc., can be considered as the context in the case of recommendation systems [10]. Most of the domains introduce context-awareness to increase the efficiency and usability of information systems particularly when such a system is accessed by mobile devices [11]. However, this is applicable to other domains as well since usability of an information system is highly concerned in development process. The context-aware recommendation systems have been categorized into two kinds: firstly, as systems that use contextual information as a criterion to filter items; and secondly, systems employing contextual information at the time users can evaluate items devised by some authors [12].

b) *Emotion in other recommendation domains*

Recently, more efforts have been made to use emotion in the recommendation process. Research has been conducted on individual domains or combining domains such as an affective computing and recommendation systems. The role of emotion in the recommendation systems' consumption chain has been discussed in three stages, namely the entry stage, the consumption stage and exit stage. All three wield great influence on human decision-making [13]. User emotion can be described by modeling it using the Universal model or Dimensional model. The universal model describes emotion categories as happiness, anger, sadness, fear, disgust, and surprise while the dimensional model uses valance, arousal and dominance. Adapting emotion as a context parameter to the recommendation system was first done by Gonzalez et al. (2007) [14]. From then on, many applications arose on this topic due to the success of various research work. Emotion-based music recommendation is one of the domain both recommendation systems and affective engineering studies are merged [15], [16], [17]. Due to the diversity and richness of music content and in context-based music recommendation systems, it often needs multidisciplinary efforts such as emotion description, emotion detection, etc., to achieve success. The movie recommendation domain has also been enriched by applying emotion to the recommendation and a few studies incorporated emotion in various stages of movie consumption [18], [7], [19]. Thus, for an example emotion in each stage is monitored and incorporated into the LDOS-CoMoDa dataset for the recommendation process with reference to emotional contexts: Mood, Dominant Emo and EndEmo [7].

c) *Travel recommendation systems*

In Table 1 below we summarize a few travel recommendation systems by focusing the attention on the contextual parameters and recommendation approaches used.

Table 1: Travel Recommendation Systems

Author	Context	Contextual Parameters	Recommendation Process
Bian (2009) [20]	User Behavior	Location, Open Hours, Close Date, Mini Time Stay, Age Range, Occupation	Bayesian network techniques and analytic hierarchy process
Castillo (2008) [21]	User Behavior	Previously visited places in user profiles	Case-based reasoning and the K-Nearest Neighborhood algorithm
Yong, Robin and Bamshad (2012) [22]	User Behavior	Trip Type, Trip duration, Origin City, Destination City, Month	CF with differential context relaxation
Soha, Tayasir and Adel (2016) [23]	Use Behavior and User Mood	Weather, Time of the day, Users Location User Mood: Happy, angry, Excited, Tired User's speed and travel direction	Genetic algorithm and Matrix factorization
Barranco, Noguera Castro, and Martinez (2012) [24]	Location and Trajectory	User's speed and travel direction	Improve recommendations by using context-aware filtering in CF
Gavalas and Kenteris (2011) [25]	Location, time, weather, user behavior	Location, time, weather	Collaborative filtering while considering contextual information in pervasive environment
Noguera, Barranco, Segura and MartiNez' (2012) [26]	Location	Location	Use both pre and post-filtering approaches
Soe Tsyr Yuan and Chun-Ya Yang (2017) [27]	User emotion	User behavior searching history, destination stores, feedback of emotional words	Use color imagery as the uniform representation of customers' expectation to facilitate the scoring and ranking

All the studies in the table attempted to incorporate various types of contextual information in the recommendation process. For example, Soe Tsyr Yuan and Chun-Ya Yang et al. (2017) in their work tried using emotion in the recommendation process, but their method to extract emotion was, based on color and imagination. Travel recommendation systems serve tourists with relevant and personalized destination suggestions for helping them to make better decisions. State of-the-art of recommendation systems can be analyzed as web-based systems or mobile-based systems, while the web-based are being the predominant type. As well depending on the service, systems' recommendation can be clustered. Suggested here are the destination and construction of a complete tourist package, recommended suitable attractions at one specific place, a detailed multi-day trip schedule, and social capabilities [28].

III. Context-Aware Recommendation

Context-aware recommendation systems try to estimate the rating function *R* by incorporating the contextual information *C* for item *I* by user *U* with initially specified user rating as follows;

$$R: User \times Item \times Context \longrightarrow Rating$$

where the *user x item* pair refers to users, who are not rated yet. Integration of emotion in the recommendation process can take three forms, these being contextual pre-filtering, contextual post-filtering, and contextual modeling according to Adomavicius et al. [29]. In the pre-filtering stage, the contextual information is used to filter and select the most relevant data before applying the recommendation algorithm. On the other hand, the post-filtering applies recommendation algorithm to the original dataset; then the recommendations are filtered according to the contextual information. Both pre-filtering and post-filtering treat the recommendation process as a 2D recommender. In our study, we only use pre-filtering techniques, since we try to compare the effectiveness of contextual modeling over contextual filtering approach. The contextual modeling approach considers the context in the recommendation algorithm and hence the rating function is treated as a 3D function which represents a user, item, and context as *User x Item x Context* and provides a rating for each user.

a) Pre-filtering with context-aware recommendation

The collaborative filtering technique uses the preference for items preferred by users (user-item matrix). Each entry in the user-item matrix represents the preference score or the ratings of the i^{th}user for the j^{th} item, where there is m number of users, $U = u_1, u_2, \ldots,$ u_m and n number of items, $I = i_1, i_2, \ldots, in$. Each user u_i has a list of items i_i, which the user has expressed his/her preference about (see Figure 1). By calculating the similarities between the users, collaborative filtering matches set of users with relevant interest and make the recommendation [30].

Predictions $P_{i,j}$, express the predicted user's preference for item j for the active user u_i. The predictive value is a numerical value which is on the same scale as the ratings provided by users.

Recommendation List is a list of top N items, that the active user u_i will prefer most and this list represents a no. of items that user hasn't preferred so far. The collaborative filtering can be two categories namely memory-based (user-based) and model-based (item-based) [31], [32].

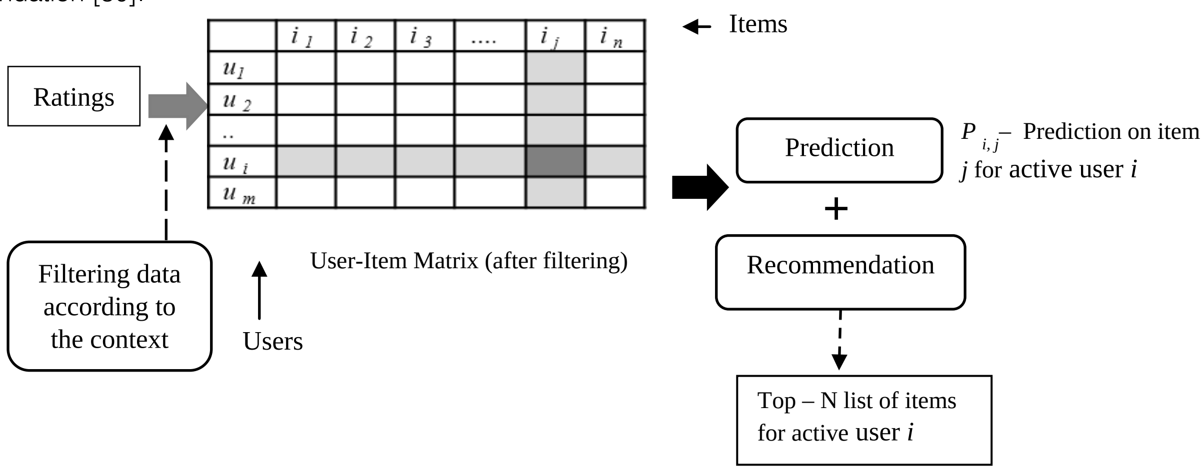

Figure 1: Collaborative Filtering Process with Pre-filtering Technique. The filtered user-item matrix data are used to predict rating for a user.

In the pre-filtering approach, the user-item matrix consisted of the filtered dataset according to the current context in the query.

b) Contextual modeling with context-aware recommendation

In applying Tensor Factorization techniques to recommendation systems, a predictive model is provided by analyzing patterns from the data, linked to the multifaceted nature of the user-item interaction. A tensor is considered to be an array of numbers with more than two dimensions and serve as a natural extension of matrices to a higher order case [33], [34]. Thus, a tensor is a multidimensional array or can refer to a N^{th} order tensor which is an element of the tensor product of N vector spaces. We use CANDECOMP/PARAFAC(CP) Tensor Factorization model which uses ratings from M users for N items under Q types of contexts as a three-dimensional tensor $M \times N \times Q$. The latent features stored in $U \in R^{M \times D}$, $I \in R^{N \times D}$ and $C \in R^{Q \times D}$ where U represents D-dimensional row vector for m users, I for latent features for item i and C represents the latent features of context category q; [35] (see Figure 2).The same size vectors are sometimes arranged together to form three matrices in Tensor Factorization model, and for the explanation, we also use it as the size of d. Then user m's rating for item i under context q can be predicted as following:

$$f_{miq} = \sum_{d=1}^{D} U_{md} I_{id} C_{qd}$$

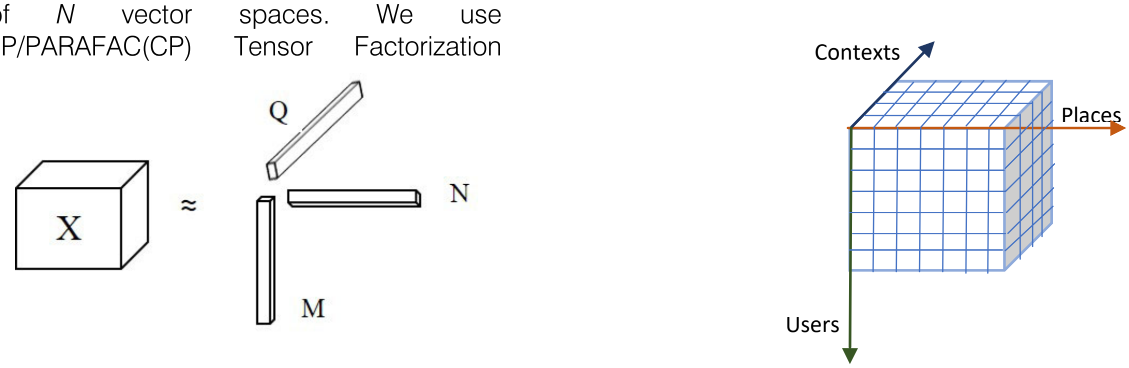

Figure 2: Tensor Factorization Model.

Global Journal of Computer Science and Technology (D) Volume XVIII Issue I Version I Year 2018

IV. Incorporation of Emotion and User Behavior in Proposed Recommendation System

a) Context acquisition

In the implementation of the proposed recommendation system, the contextual parameters must be acquired and make available for recommendation.

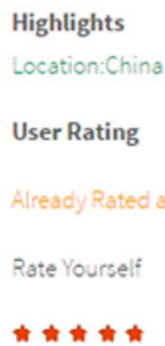

Figure 3: User Rating Capturing. User preference for a place gathered in five-star scale.

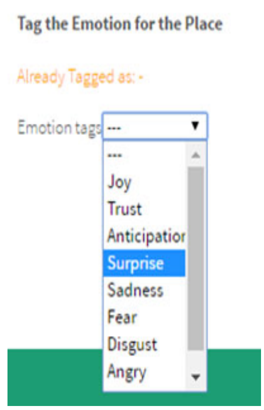

Figure 4: Emotion Tag Creation. The users were asked to tag an emotion for a place when they logged into the system.

The emotion of the users recorded in the system when users logged into it by themselves. Users' current emotions are collected according to the scale of *Happy, Surprise, Disgust, Sad, Afraid, Angry, Confidence* and *Anticipation* based on the Plutchik emotion classification [36]. Concerning user behavior, we recorded user actions such as user rating and emotion tagging for places in the system as illustrated in Figures 3 and 4.

b) Dataset

The dataset used to implement the proposed recommendation system was derived by collecting data for the world's most famous 100 tourist attractions in 2016. This information included place description, location and images and they were collected from Wikipedia[1]while the average rating and one hundred user reviews for each place were collected from TripAdvisor[2]. Then the extracted reviews were analyzed and classified to acquire emotion tags to represent a user's emotional state for a place in two stages. Firstly, stop words were removed, stemming was done using Porter's algorithm and Term Frequencies (TF) were calculated for each review and calculated the total TFs by emotions and with highest frequencies we decided the emotion tag [46]. We collected 9998 ratings for 8470 users, rated on 100 places and derived an emotion tag for each user rated by each place.

c) Recommendation system implementation

The implementation of the proposed recommendation system was done based on the selected two approaches, Pre-filtering and Tensor Factorization. We developed two recommendation engines for the system which were, based on collaborative filtering and Tensor Factorization, using the two derived datasets and loaded the place data into the system's database. The proposed framework for the recommendation process with each approach illustrated in Figure 5. The collaborative filtering approach considers the recommendation process with emotion (CFE), user behavior (CFUB) and emotion and user behavior (CFEEUB) together with the Pre-filtering techniques in the proposed context-aware recommendation system. The similarity and predictive rating values were calculated for each user, and the top five places were recommended to the user for each CFE, CFUB, and CFEUB approaches. To compare the effectiveness in recommendation process, the system which is not incorporated with any contextual parameter (CFN) also developed. In the implementation process, we used item-item collaborative filtering to develop and review our contextual parameters on the derived dataset for pre-filtering techniques.

[1]https://en.wikipedia.org
[2]https://www.tripadvisor.com

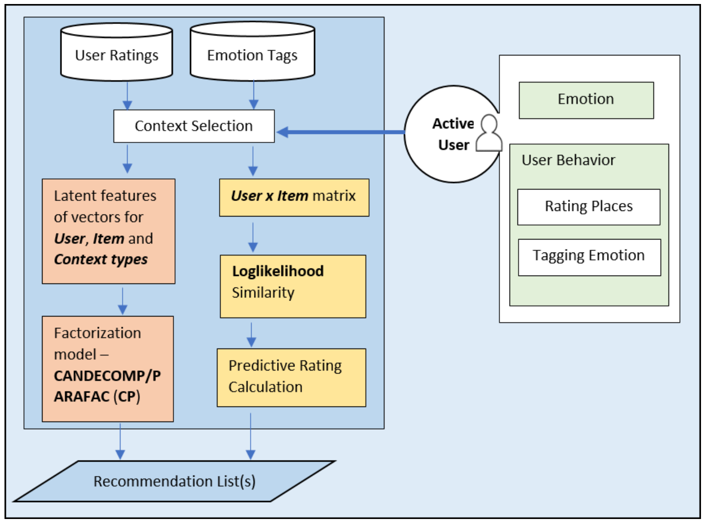

Figure 5: Architecture for the Recommendation System with two Recommendation Approaches. The Tensor factorization follows the CP factorization model while item-item collaborative filtering was used as the Pre-filtering technique.

In the context-aware recommendation process the recommendation based on, emotion was analyzed with reference to three emotion groups based on the Plutchik's emotion classification: Group I: Anticipation (Anticipation, Surprise), Group II: Joy (Joy, Sadness, Fear) and Group III: Trust (Trust, Disgust and Anger). Thus in the collaborative filtering recommendation process, selecting data to be placed in the recommendation engine was done based on these three groups since we assumed that the recommendation should lie on the positive emotion scale. Therefore, Disgust, Fear, Anger, and Sadness are categorized and arranged as three positive groups, i.e., Anticipation, Joy and Trust based on Plutchik's comprehensive list of eight primary emotions arranged as opposing pairs. To refrain from using the negative emotion category in each group, Fear and Anger arranged in the Joy and Trust groups, respectively. We utilized these three groups to evaluate the influence of user emotion on the recommendation. The dataset was input to the recommendation function based on the user's emotion states that were logged in to the system.

To apply Pre-filtering with item-item collaborative filtering, the target user's rating prediction for a target item is made by considering the user-item rating pairs, while the prediction for a certain user for a target item is predicted based on the user's ratings on the observed items. The similarity calculation for item *i* and item *j*, needs to identify set of users who have rated for both items and then compute the similarities for those users [37], [38].

The similarity calculation for the recommendation process was calculated based on the Loglikelihood ratio which relies on calculating the similarity between two items or users based on statistics since the Loglikelihood provided a sufficient number of items for recommendation compared to Pearson's Correlation. The Loglikelihood ratio is derived based on the occurrences relating to the users or items which are users or items overlapping in preferences where both compared users have preferences or not, and the events where both users or items do not have preferences [39], [40].The prediction algorithms play the role of guessing the rating a user would provide for a target item [41]. We calculated the predictive rating $P_{u,i}$, by after a space user u for item i as shown below:

$$P_{u,i} = \frac{\sum_{n\in N}(sim\,(u,n)+1)\ \times\ R_{u,n}}{\sum_{n\in N}\,(sim(u,n)+1)}$$

where *sim (u, n)* is the similarity between n^{th} item and user *u* and $R_{u,n}$ is the rating for user *u* on item n for all *N* number of items which are based on the Mahout item based recommendation algorithm [42]. The similarity calculations ranged from -1.0 to 1.0 and to avoid negative values we added 1.0 to similarity values, so the similarity ranges from 0.0 to 2.0. The top five place recommendations list was created based on the highest similarity values to the least in the provided most similar places, set from the places pool. Pu_1, s_1 is the illustration for predictive rating calculation in different contexts. (see Figure 6,7 and 8).

	S1	S2
U1	1	0.45
U2	1	0.5

Figure 6: User-Item matrix U1 and u2 are two users rated for item s1 and s2.

	S1	S2
U1	1	1
U2	0	1

Figure 7: User-emotion matrix

	S1	S2
U1	0	1
U2	1	1

Figure 8: User-user behavior matrix

$$P\ u_1, s_1(\text{Emotion}) = ((1+1)*1+(0.45+1)*1)/(1+0.45) = 1.7$$

$$P\ u_1, s_1(\text{User behavior}) = ((1+1)*0+(0.45+1)*1)/(1+0.45) = 1$$

In the contextual modeling approach, we used Tensor Factorization, because in applying it enhances the ability to consider the multifaceted nature of the user-item interaction as discussed in the Background. In the CP Tensor Factorization, three-dimensional tensors *M x N x Q* are used for *M* users for *N* items with the *Q* types of contexts. Two proposed contextual parameters were analyzed as Tensor Factorization with emotion (TFE), Tensor Factorization with user behavior (TFUB) and Tensor Factorization with emotion and user behavior (TFEUB) in Tensor Factorization approach. So, in each case, at least one parameter was selected for the recommendation process. The recommendation of the tensor-based approach was developed based on CARSkit library [43] and the context appearance for user *m* for item *i* with the context *k* can be either 1 or 0 as a binary value and input to the recommendation process. As an example, for user 4 for Place ID 52, the contextual information is stated below in Table 2.

Table 2: Example of the Results for Contextual Information for a User

		emotion: angry	emotion: anticipation	emotion: disgust	emotion: fear	emotion: joy	emotion: sadness	emotion: surprise	emotion: trust	rated	taggedemo
TFEUB	4	0	0	0	0	0	0	1	0	1	1
TFUB	5	0	0	0	0	0	0	0	0	1	1
TFE	3	0	1	0	0	0	0	0	0	0	0

Figure 9 depicts an example for top five place list provided for a user in Tensor Factorization approaches.

Figure 9: Recommendation Lists. The recommended lists in the figure show places provided by three recommendation approaches TFE, TFUB, and TFEUB

V. Evaluation

a) Experimental setup

First, we describe the evaluation protocols for place recommendation in the proposed system. Then we demonstrate how the contextual parameter selection for Pre-filtering and Tensor factorization performed to assess the effectiveness of the recommendation process. Afterwards, we evaluate the impact of each parameter on each approach in the recommendation process in terms of the recommendation system's quality. For comparison reasons, we separately evaluate each recommendation approach, and especially the collaborative filtering approach against non-context collaborative filtering based recommendation. Also, for each context, the Tensor Factorization and Collaborative Filtering approaches were also compared. The reason for selecting both Tensor Factorization and Collaborative Filtering is because both filtering and contextual modeling approaches can be tested in context-aware recommendation.

The implemented system, *Travel Destination* was presented to 16 users, and they were all asked to experiment with the recommendation process and evaluate the two recommended lists. These lists, which were asked for rating according to the user preference for each place in the list and state the overall preference for the list according to user's current emotion while stating the overall satisfaction for the recommended lists in the five- point Likert scale.

b) Evaluation protocols

Evaluation Protocols for the task of recommendation lists, the following are used:

1) We used Precision and Mean Average Precision (MAP) values of the two approaches.
2) We evaluated the recommendation lists considering the emotion groups derived at the recommendation engine designing stage to track, how the lists fitted with the users' emotions by using Mean Average Precision on Emotional groups(MAPE).
3) To compare contextual recommendation against non-context recommendation we used t-test to examine the superiority of the all context incorporated approaches (CFE, CFUB, CFEUB, TFE, TFUB,TFEUB) against baseline approach (CFN) by evaluating t_{mean} of both Average precision (*AveP*) and Average Preference Rating (*APR)* based on the rating, users marked as Preferred and Preferred much in the five-point Likert scale.
4) The user rating behavior variation for the user emotion was analyzed for the validation of the emotion groups in the recommendation system design.
5) The overall satisfaction of users towards the recommendation system also was analyzed.

Thus, in the experiment, the testing users had to register to the system and then input their emotions in the given emoticon scale and evaluate the two lists, each with five places.

c) Results and discussion

The Classification Accuracy Measure is one of the Accuracy metrics, which measures to what extent a recommendation algorithm can correctly classify items as interested or not. In our study, we use *Precision* one of the common measurers for recommendation system evaluation; recommender system's preference ratings must be converted its rating scale into a binary scale, so we converted rating scale as ratings of 4 and 5 are good recommendations [44]. The Precision expresses the fraction of recommended items that are actually relevant to the user [45].

$$\text{Precision} = \frac{\text{Correctly recommended items}}{\text{Total recommended items}}$$

The precision values for the all the context incorporated approaches (CFE, CFUB, CFEUB, TFE, TFUB, TFEUB) and the non-context approach (CFN) as rated by 16 users, were calculated as below and mean precision values for the all the context incorporated approaches were greater compared to CFN. The Average Precision calculates the precision at the position of every correct item in the ranked results list of the recommender. The mean of these average precision values across all relevant lists is the mean average precision or *MAP*. The *MAP* also outperformed the all the context incorporated approaches compared to CFN (see Table 3).

$$AveP = \frac{\sum_{k=1}^{n}(P(k) \times rel(k))}{\text{number of relevant items}}$$

$$MAP = \frac{\sum_{q=1}^{q} AveP(q)}{Q}$$

where *P(k*) is the precision at k-th element, *rel(k)* is 1 if the i-th item of the list is relevant, and *Q* is the total no. of lists.

Table 3: Precision Values, and Mean Average Precision Values

Algorithm	Precision	Mean Av. Precision
CFN	59.69	61.98
CFUB	61.88	67.28
CFE	65.31	69.83
CFEUB	71.88	79.18
TFUB	63.75	72.27
TFE	68.75	74.81
TFEUB	72.5	81.59

Moreover, we analyzed the Mean Average Precision based on emotional groups (*MAPE*) for each approach.

$$MAPE = \frac{\sum_{c=1}^{C} \sum_{q=1}^{q} AveP(q)}{\sum_{c=1}^{C} Q}$$

where C is the no. of emotion groups, and we rely on three groups in our evaluation. In Figure 10, The overall *MAPE* values on Collaborative Filtering approach and Tensor Factorization approach with emotional groups Trust, Joy and Anticipation are illustrated respectively. Thus, the emotional group vise *MAP* showed increased results compared to general approach.

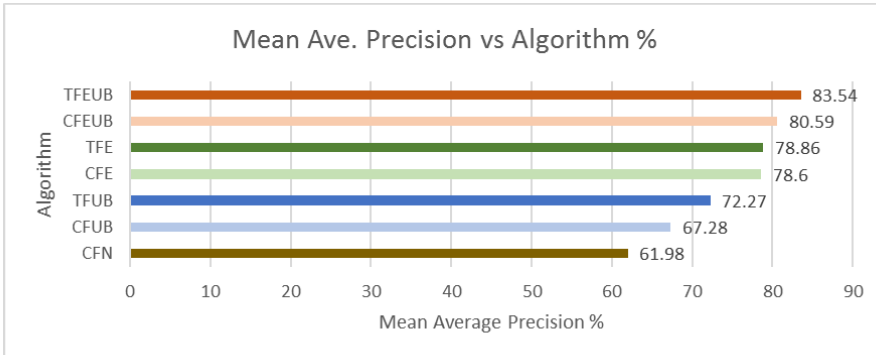

Figure 10: Average Precision Values with Emotion Groups

We, statistically compared the performance of the Collaborative Filtering approaches and Tensor Factorization approaches with non-context approach CFN; in terms of average precision values and average preference ratings. So, the hypotheses are:

- H_0: $\mu_c = \mu_{CFN}$ and alternative hypotheses are H_a: $\mu_c \neq \mu_{CFN}$, H_a: $\mu_c > \mu_{CFN}$. where μ_c and μ_{CFN} are Mean of average precision rating of context-aware approaches and non-context collaborative filtering approach respectively.
- H_0: $\mu_{cp} = \mu_{CFN}$ and alternative hypotheses are H_a: $\mu_{cp} = \mu_{CFN}$,H_a: $\mu_{cp} > \mu_{CFN}$. where μ_{cp} and μ_{CFN} are Mean of preference ratings of context-aware approaches and non-context collaborative filtering approach respectively.

Since T value (Test Statistic) $< t_{\alpha,\ v}$(Critical Value), we reject the null hypothesis in both cases and concluded that the two population means are different at the 0.05 level of significance, while at the alternative hypothesis $\mu_c > \mu_{CFN}$ and $\mu_{cp} > \mu_{CFN}$ are true in all contexts incorporated approaches. Table 4 illustrates *p-values* obtained for the t-test from the *MAP* and *Mean Rating Preferences*.

Table 4: Precision Values and Mean Average Precision Values

Algorithm	Mean Average Precision (p-value)	Mean Rating Preference (p-value)
CFUB	0.6221	0.8386
CFE	0.4389	0.5094
CFEUB	0.1012	0.0940
TFUB	0.2614	0.2408
TFE	0.1631	0.7061
TFEUB	0.039	0.2018

Therefore, the t-test results showed that the difference with the baseline recommender (CFN) in terms of average precision and average rating preferences of the contextual approaches are statistically significant. The user rating behavior showed that users have rated as preferred and much preferred when they have Joy, Surprise, Trust and Anticipation emotion, compared to Fear, Sad, Disgust and Angry emotions. Thus, these results showed that suggesting places, incorporated with positive emotion is much suitable and the used emotional group classification in the recommendation system design process, works fine in this regard (see Figure 11).

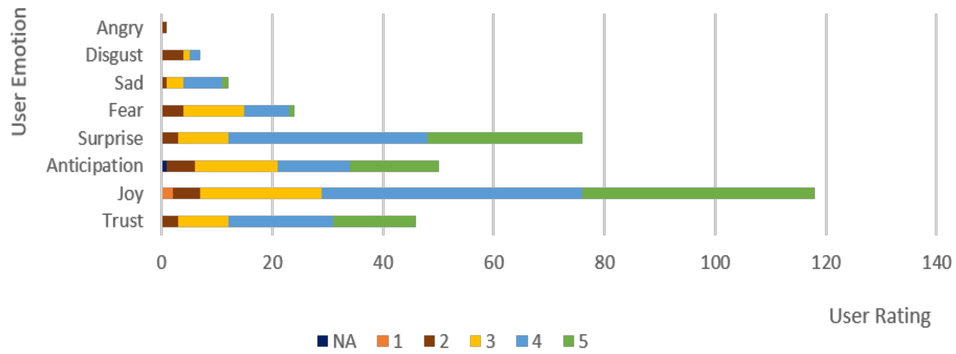

Figure 11: User Rating Behavior based on User Emotion

Finally, we collected users' feedback on how they overall satisfied with the recommended place list, their opinion based on their current emotion stated as shown in Table 5. According to the results, CFEUB and TFEUB lists are highly preferred by users as well matched with their current emotions.

Table 5: Preference Values for Algorithms for the Top Five Places

Algorithm	Overall preference	Preference with the emotion of user
CFN	46.77	-
CFUB	80	-
CFE	60	53.33
CFEUB	87.5	87.5
TFUB	68.75	-
TFE	73.33	80
TFEUB	73.33	86.67

VI. Conclusion and Future Work

In this study, we analyzed the effectiveness of using user emotion and behavior in context-aware tourist destination recommendation. This was achieved by utilizing Pre-filtering and Tensor Factorization techniques in the recommendation process. User emotion and behavior are much employed in classical recommendation domains like music, movies, and books, but the travel destination recommendation is still in the early stages of development in using the selected parameters. Since adapting emotion in the consumption stage of the recommendation is difficult, in our study we focused on the effectiveness of using emotion along with user behavior in the proposed recommendation. Our system can outperform several state-of-the-art context-aware travel recommendation systems. In both Pre-filtering and Tensor Factorization incorporation of context outperformed well. We employed Plutchik's emotion classification for both emotion word detection derived from reviews and acquired users' current emotions into the system. Based on the emotion selected by the user, we suggested that the recommended place list should consist of positive emotion categories: Joy, Anticipation, and Trust.

References

1. Resnick, P., & Varian, H. R. (1997). Recommender systems. Communications of the ACM, 40(3), 56-58.
2. Tkalčič, M., De Carolis, B., De Gemmis, M., Odić, A., & Košir, A. (Eds.). (2016). Emotions and personality in personalized services: models, evaluation and applications. Springer.
3. Baltrunas, L., & Amatriain, X. (2009, October). Towards time-dependant recommendation based on implicit feedback. In Workshop on context-aware recommender systems (CARS'09).
4. Domingues, M. A., Jorge, A. M., & Soares, C. (2011). Using contextual information as virtual items on top-n recommender systems. arXiv preprint arXiv:1111.2948.
5. Böhmer, M., Bauer, G., & Krüger, A. (2010, September). Exploring the design space of context-aware recommender systems that suggest mobile applications. In 2nd Workshop on Context-Aware Recommender Systems (Vol. 5).
6. Lombardi, S., Anand, S. S., & Gorgoglione, M. (2009). Context and customer behaviour in recommendation.
7. Zheng, Y., Mobasher, B., & Burke, R. D. (2013). The Role of Emotions in Context-aware Recommendation. Decisions@ RecSys, 2013, 21-28.
8. Ricci, F., Rokach, L., & Shapira, B. (2011). Introduction to recommender systems handbook. In Recommender systems handbook (pp. 1-35). springer US.
9. Dey, A. K. (2001). Understanding and using context. Personal and ubiquitous computing, 5(1), 4-7.
10. Campos, P. G., Fernández-Tobías, I., Cantador, I., & Díez, F. (2013, August). Context-aware movie recommendations: an empirical comparison of pre-filtering, post-filtering and contextual modeling approaches. In International Conference on

approaches. In International Conference on Electronic Commerce and Web Technologies (pp. 137-149). Springer, Berlin, Heidelberg.
11. Lemos, F., Carmo, R., Viana, W., & Andrade, R. (2012). Towards a context-aware photo recommender system. In Context-aware recommender system workshops.
12. Marinho, F. G., Andrade, R. M., Werner, C., Viana, W., Maia, M. E., Rocha, L. S., ... & Aguiar, S. (2013). MobiLine: A Nested Software Product Line for the domain of mobile and context-aware applications. Science of Computer Programming, 78(12), 2381-2398.
13. Tkalcic, M., Kosir, A., & Tasic, J. (2011, October). Affective recommender systems: the role of emotions in recommender systems. In Proc. The RecSys 2011 Workshop on Human Decision Making in Recommender Systems (pp. 9-13).
14. Gonzalez, G., De La Rosa, J. L., Montaner, M., & Delfin, S. (2007, April). Embedding emotional context in recommender systems. In Data Engineering Workshop, 2007 IEEE 23rd International Conference on (pp. 845-852). IEEE.
15. Cai, R., Zhang, C., Wang, C., Zhang, L., & Ma, W. Y. (2007, September). Musicsense: contextual music recommendation using emotional allocation modeling. In Proceedings of the 15th ACM international conference on Multimedia (pp. 553-556). ACM.
16. Han, B. J., Rho, S., Jun, S., & Hwang, E. (2010). Music emotion classification and context-based music recommendation. Multimedia Tools and Applications, 47(3), 433-460.
17. Shan, M. K., Kuo, F. F., Chiang, M. F., & Lee, S. Y. (2009). Emotion-based music recommendation by affinity discovery from film music. Expert systems with applications, 36(4), 7666-7674.
18. Wakil, K., Bakhtyar, R., Ali, K., & Alaadin, K. (2015). Improving Web Movie Recommender System Based on Emotions. (IJACSA) International Journal of Advanced Computer Science and Applications, 6(2).
19. Ho, A. T., Menezes, I. L., & Tagmouti, Y. (2006). E-mrs: Emotion-based movie recommender system. In Proceedings of IADIS e-Commerce Conference. USA: University of Washington Both-ell (pp. 1-8).
20. Huang, Y., & Bian, L. (2009). A Bayesian network and analytic hierarchy process based personalized recommendations for tourist attractions over the Internet. Expert Systems with Applications, 36(1), 933-943.
21. Castillo, L., Armengol, E., Onaindía, E., Sebastiá, L., González-Boticario, J., Rodríguez, A., ... & Borrajo, D. (2008). SAMAP: An user-oriented adaptive system for planning tourist visits. Expert Systems with Applications, 34(2), 1318-1332.
22. Zheng, Y., Burke, R., & Mobasher, B. (2012). Differential context relaxation for context-aware travel recommendation. E-Commerce and Web Technologies, 88-99.
23. Mohamed, S. A., Soliman, T. H. A., & Sewisy, A. A. (2016). A context-aware recommender system for personalized places in mobile applications. Int. J. Adv. Comput. Sci. Appl, 7(3), 442-448.
24. Barranco, M. J., Noguera, J. M., Castro, J., & Martínez, L. (2012). A context-aware mobile recommender system based on location and trajectory. Management intelligent systems, 153-162.
25. Gavalas, D., & Kenteris, M. (2011). A web-based pervasive recommendation system for mobile tourist guides. Personal and Ubiquitous Computing, 15(7), 759-770.
26. Noguera, J. M., Barranco, M. J., Segura, R. J., & MartíNez, L. (2012). A mobile 3D-GIS hybrid recommender system for tourism. Information Sciences, 215, 37-52.
27. Yuan, S. T., Yuan, S. T., Yang, C. Y., & Yang, C. Y. (2017). Service recommender system based on emotional features and social interactions. Kybernetes, 46(2), 236-255.
28. Borràs, J., Moreno, A., & Valls, A. (2014). Intelligent tourism recommender systems: A survey. Expert Systems with Applications, 41(16), 7370-7389.
29. Adomavicius, G., & Tuzhilin, A. (2015). Context-aware recommender systems. In Recommender systems handbook (pp. 191-226). Springer US.
30. J. L. Herlocker, J. A. Konstan, L. G. Ter-veen, J. T. Riedl, Evaluating collaborative filtering recommender systems, ACM Transactions on Information Systems (TOIS) 22 (1) (2004) 5-53.
31. Breese, J. S., Heckerman, D., & Kadie, C. (1998, July). Empirical analysis of predictive algorithms for collaborative filtering. In Proceedings of the Fourteenth conference on Uncertainty in artificial intelligence (pp. 43-52). Morgan Kaufmann Publishers Inc..
32. Konstan, J. A., Miller, B. N., Maltz, D., Herlocker, J. L., Gordon, L. R., & Riedl, J. (1997). GroupLens: applying collaborative filtering to Usenet news. Communications of the ACM, 40(3), 77-87.
33. Comon, P. (2014). Tensors: a brief introduction. IEEE Signal Processing Magazine, 31(3), 44-53.
34. Grasedyck, L., Kressner, D., & Tobler, C. (2013). A literature survey of low-rank tensor approximation techniques. GAMM-Mitteilungen, 36(1), 53-78.
35. Kolda, T. G., & Bader, B. W. (2009). Tensor decompositions and applications. SIAM review, 51(3), 455-500.
36. Plutchik, R., & Kellerman, H. (1980). Emotion, Theory, Research, and Experience: Theory, Research and Experience. Academic press.

37. Gong, S. (2010). A collaborative filtering recommendation algorithm based on user clustering and item clustering. JSW, 5(7), 745-752.
38. Su, X., & Khoshgoftaar, T. M. (2009). A survey of collaborative filtering techniques. Advances in artificial intelligence, 2009, 4.
39. Dunning, T. (1993). Accurate methods for the statistics of surprise and coincidence. Computational linguistics, 19(1), 61-74.
40. Hsieh, M. Y., Chou, W. K., & Li, K. C. (2017). Building a mobile movie recommendation service by user rating and APP usage with linked data on Hadoop. Multimedia Tools and Applications, 76(3), 3383-3401.
41. Papagelis, M., & Plexousakis, D. (2005). Qualitative analysis of user-based and item-based prediction algorithms for recommendation agents. Engineering Applications of Artificial Intelligence, 18(7), 781-789.
42. Schelter, S., & Owen, S. (2012). Collaborative filtering with apache mahout. Proc. of ACM RecSys Challenge.
43. Zheng, Y., Mobasher, B., & Burke, R. (2015, November). Carskit: A java-based context-aware recommendation engine. In Data Mining Workshop (ICDMW), 2015 IEEE International Conference on (pp. 1668-1671). IEEE.
44. Shani, G., & Gunawardana, A. (2011). Evaluating recommendation systems. Recommender systems handbook, 257-297.
45. Isinkaye, F. O., Folajimi, Y. O., & Ojokoh, B. A. (2015). Recommendation systems: Principles, methods and evaluation. Egyptian Informatics Journal, 16(3), 261-273.
46. Ishanka, U. A., & Yukawa, T. (2017). The Prefiltering Techniques in Emotion Based Place Recommendation Derived by User Reviews. Applied Computational Intelligence and Soft Computing, 2017.