Adapt to Emotional Reactions In Context-aware Personalization

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ABSTRACT

Context-aware recommender systems (CARS) have been developed to adapt to users' preferences in different contextual situations. Users' emotions have been demonstrated as one of effective context information in recommender systems. However, there are no work exploring the effect of emotional reactions (or expressions) in the recommendation process. In this paper, we assume that users may give similar ratings even if they present different emotional reactions or expressions on the movies. We further model the traits of emotional reactions and incorporate them into context-aware matrix factorization as regularization terms. Our experimental results based on the LDOS-CoMoDa movie data set validate our assumptions and prove that it is useful to take emotional reactions into consideration in context-aware recommendations.

Keywords

context, recommendation, emotion, emotional reactions

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Information filtering, Retrieval models; H.1.2 [**Models and Principles**]: User/Machine Systems - *human information processing*

1. INTRODUCTION AND BACKGROUND

Recommender systems (RS) are an effective way in alleviating information overload by tailoring recommendations to users' personal preferences. Context-aware recommender systems (CARS) take contextual factors (such as time, location, companion, occasion, etc) into account in modeling user profiles and in generating recommendations. For example, users' choice on movies may be very different if the user is going to watch the movie with *children* rather than with his or her *partner*.

Context, is usually defined as, "*any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves* [12]". In CARS, we view the dynamic attributes as the observed contexts which may change when the user performs the same activity repeatedly [38]. For example, the *time* and *location* may change every time when a user tries to watch a movie. The *season* or *trip type* may change when a user is going to reserve a hotel. In addition to these factors, users' emotional states are one of these dynamic variables. And emotions may change anytime in the process of user interactions with the items or the applications. These emotional information have been demonstrated as effective and influential context in previous research [45, 44].

Emotional reactions or expressions are highly correlated with the traits of user personalities. Personality accounts for the most important ways in which individuals differ in their enduring emotional, interpersonal, experimental, attitudinal and motivational styles [24]. In the domain of recommender systems, personality can be viewed as a user profile, which may be context-independent and domain-independent. Both emotional information [18, 11, 34, 45] and user personality [31, 19, 35] have been successfully incorporated into recommender systems by existing research.

Our previous research [45] has successfully utilized emotional variables as contexts in recommender systems to improve recommendation performance. Unfortunately, as far as we know, there are no research on exploring the effect of emotional reactions or expressions. We believe that users' emotional reactions or expressions are also useful to model users' preferences or rating behaviors in real practice. For example, two different users may give high ratings on a same tragedy drama movie. One of them indicated his or her emotional state as "*happy*" when finishing the movie, because this user thought it was a really good movie. By contrast, another user may express his or her feeling as "*sad*" since the user was impressed or moved by the tragedy movie. As a result, the two users have same rating behaviors on the movie but with different emotional reactions or expressions. One of the potential reasons is that different user personalities may result in different ways or habits for users to express their emotions.

Therefore, the users' rating profiles associated with different (or even opposed) emotional reactions therefore could be useful to assist recommendations. In this paper, we propose to incorporate emotional reactions (or expressions) as regularization terms in the context-aware matrix factorization approach, and further explore its effect on the performance of context-aware recommendations.

The following sections are organized as follows: Section 2 introduces related work, including the background of context-aware recommendation, and the role of emotions and personality in recommender systems. Section 3 gives the preliminary description of essential information, such as the LDOS-CoMoDa movie data which contains emotional variables, and the introduction about the CAMF technique. Section 4 discusses our methodology that incorporates the emotional reactions as regularization terms

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into the CAMF approach. Section 5 describes our experimental results and discussions, followed by Section 6 which concludes our findings and discusses our future work.

2. RELATED WORK

One of the goals in the recommender systems (RS) is to assist users' decision making by providing a list of recommendations. Due to the fact that users' choice usually varies from time to time and from context to context, context-aware recommender systems (CARS) [2, 1] are promoted and developed to adapt to users' preferences in different contextual situations.

In rating-based RS applications, such as movie or book ratings, the standard formulation of the recommendation problem begins with a two dimensional matrix of ratings, organized by user and item: *Users* $\times$ *Items* $\rightarrow$ *Ratings*. The key insight of CARS is that users' preferences on items may be also a function of the context in which those items are encountered. Incorporating contexts requires that we estimate user preferences using a multidimensional rating function, *Users* $\times$ *Items* $\times$ *Contexts* $\rightarrow$ *Ratings* [1].

In the past decade, several context-aware recommendation algorithms have been developed. By additionally incorporating context information, these algorithms have been demonstrated to be useful to improve recommendation performance in numerous domains, such as e-commerce [28, 15], movies [33, 26, 10], music [3, 16], restaurants [30, 27], travels [39, 8], educational learning [37], mobile applications [4, 6], and so forth. The context variables adopted in those applications are domain-specific ones. And the most widely used context information are the time of the day, the day of the week, and location information which can be easily captured from ubiquitous environment, such as Web logs, mobile devices, sensors.

It is well known that human decision making is subject to both rational and emotional influences [14]. The field of affective computing takes this fact as basic to the design of computing systems [29]. The role of emotions in recommender systems was recognized by the research community as early as 2005 [23], giving rise to research in emotion-based movie recommender systems [18] and the impact of emotions in group recommender systems [23, 11]. This results in the highlight of research on affective recommender systems [34] which have been proved to be useful on recommendation performance in several domains, such as music [22, 32, 9] and movies [7, 25, 18].

Emotional states, accordingly, are also viewed and used as contexts in recommender systems. Shi et al. [33] mined the mood similarity to assist context-aware movie recommendation. Odic, et al. [26] identified the significant contributions by emotional variables compared with other contextual factors in the LDOS-CoMoDa movie rating data. Mood information can also be used for television and video content recommendation [36]. Baltrunas, et al. [3] adopted mood as context to assist context-aware music recommendation. The role of emotions in context-aware recommendation is summarized in [45, 44] which helps additionally discover insights about why and where emotional states play an important role in the recommendation process.

Emotional states are usually dynamic and may change from time to time. Based on the introduction about the affective recommender systems [34], the emotional information in three stages may be useful: entry stage (i.e., before the activity), consumption stage (i.e., during the activity) and exit stage (i.e. after the activity). In this case, emotional reactions can be captured across these three stages. As introduced previously, users may present different emotional reactions, but actually they leave the same or similar ratings on the items. In this paper, we make the first attempt to explore the effect of emotional reactions in the context-aware recommendations.

3. PRELIMINARY

To further discuss the topics in the context-aware recommendation, it is necessary to introduce some terminologies:

Table 1: Sample of a Context-aware Movie Rating Data Set

User	Movie	Rating	Time	Location	Companion
U1	T1	5	Weekday	Home	Kids
U1	T1	3	Weekend	Cinema	Family
U2	T2	3	Weekday	Cinema	Partner
U2	T3	4	Weekday	Home	Kids
U3	T4	2	Weekend	Home	Partner

Table 1 shows an example of context-aware movie data which contains five rating profiles given by three users on four movies in different contextual situations. In our discussions, we will use the term *contextual dimension* to denote the contextual variable, such as "Location", "Time" and "Companion". The term *contextual condition* refers to a specific value in a contextual dimension, e.g. "Home" and "Cinema" are two contextual conditions for the dimension "Location". *Context* or *contextual situation* therefore refers to a combination of contextual conditions, e.g., {Weekday, Home, Kids}.

Next, we introduce the LDOS-CoMoDa movie data [1] which is a data set with multiple contextual dimensions including several emotional variables. We also introduce context-aware matrix factorization which is a popular algorithm in CARS and we use it as a base algorithm in this paper.

3.1 LDOS-CoMoDa Data Set

In the domain of context-aware recommendation, there are very limited number of data sets available for public research, not to mention the data that contains emotional variables. The LDOS-CoMoDa data set [21] introduced below is one of the data sets that was collected from user surveys, and can be used for this type of research in this paper. The data has 2291 ratings (rating scale is 1 to 5) given by 121 users on 1232 items within 12 contextual dimensions. The description of the contextual dimensions and conditions can be described by Table 2.

Table 2: List of Context Information in the LDOS-CoMoDa Data

Dimension	Contextual Conditions
Time	Morning, Afternoon, Evening, Night
Daytype	Working day, Weekend, Holiday
Season	Spring, Summer, Autumn, Winter
Location	Home, Public place, Friend's house
Weather	Sunny / clear, Rainy, Stormy, Snowy, Cloudy
Companion	Alone, Partner, Friends, Colleagues, Parents, Public, Family
endEmo	Sad, Happy, Scared, Surprised, Angry, Disgusted, Neutral
domEmo	Sad, Happy, Scared, Surprised, Angry, Disgusted, Neutral
Mood	Positive, Neutral, Negative
Physical	Healthy, Ill
Decision	Movie choices by themselves or users were given a movie
Interaction	First interaction with a movie, Nth interaction with a movie

Among these 12 contextual dimensions, there are three ones that can be considered emotional dimensions: endEmo, domEmo and mood. "endEmo" is the emotional state experienced at the end of the movie (i.e., emotion in the exit stage). "domEmo" is

[1]LDOS-CoMoDa data set, http://www.ldos.si/comoda.html

the emotional state experienced the most during watching (i.e., emotion in the consumption stage). "mood" is the emotion of the user during that part of the day when the user watched the movie (i.e., emotion in the entry stage). "EndEmo" and "domEmo" contain the same seven conditions: *Sad, Happy, Scared, Surprised, Angry, Disgusted, Neutral*, while "mood" only has three simple conditions: *Positive, Neutral, Negative*.

Context selection is usually performed before we apply any context-aware recommendation algorithms. We'd like to retain the most influential context dimensions, since irrelevant ones may introduce noises in the data and further hamper the recommendation accuracy. Based on the statistical selection method introduced in [26], we only use 7 out of the 12 contextual dimensions in our experiments: time, daytype, location, companion and the three emotional variables.

The three emotional variables (i.e., mood, domEmo and endEmo) describe users' affective states during the user interactions with the movies in terms of three stages respectively: entry stage, consumption stage and exit stage as introduced in [34]. In other words, mood can be viewed as current context before the user starts watching the movie. By contrast, domEmo and endEmo can indicate future emotional states during the user's interactions with the activity of movie watching. These future status can also be viewed as contexts too if we interpret them as user intents. For example, a user is feeling sad now, and he or she wants to select a movie to watch in order to be happy. In this example, "sad" is the current user mood, and "happy" can be viewed as user's future emotional state, such as in the domEmo or endEmo.

3.2 Context-aware Matrix Factorization

One of the most popular context-aware recommendation algorithms is the one built upon matrix factorization, namely, the context-aware matrix factorization (CAMF) approach [5]. There are different variants of CAMF, here we introduce the CAMF_CU approach which incorporate a user-personalized contextual rating bias into matrix factorization. More specifically, the rating prediction function by CAMF_CU can be described by Equation 1.

$$\hat{r}_{uic_1c_2...c_N} = \mu + \sum_{j=1}^{N} B_{u,c_j} + b_i + p_u^T q_i \tag{1}$$

Assume there are totally N contextual dimensions. $c_1c_2..c_N$ is used to denote a contextual situation, where c_1 indicates the value of contextual condition in the 1^{st} context dimension. $\hat{r}_{uic_1c_2...c_N}$ therefore represents the predicted rating for user u on item i in the situation $c_1c_2..c_N$. The prediction function is composed of four components: the global mean rating μ, item rating bias b_i, the aggregated contextual rating bias $\sum_{j=1}^{N} B_{u,c_j}$, and user-item interaction represented by the dot product of a user vector and item vector, $p_u^T q_i$. p_u is the user vector represented by a set of latent factors, and q_i is the item vector represented by the same set of factors. p_u can tell how much the user u likes those latent factors, while q_i indicates how the item i obtains these factors. Therefore, the dot product function is used to estimate how much the user will like this item.

The term B_{u,c_j} is the estimated contextual rating bias for user u in context condition c_j. It is used to denote how user u's rating is deviated in each contextual condition.

$$err = r_{uic_1c_2...c_N} - \hat{r}_{uic_1c_2...c_N} \tag{2}$$

$$\min_{B_*, b_*, p_*, q_*} \sum_{r \in R} \left[\frac{1}{2} err^2 + \frac{\lambda}{2} \left(\sum_{j=1}^{N} B_{u,c_j}^2 + b_i^2 + ||p_u||^2 + ||q_i||^2 \right) \right] \tag{3}$$

Afterwards, the algorithm is able to learn the corresponding parameters by minimizing the squared errors in prediction. The loss function as shown in Equation 3 is a composition of squared error and regularization terms which are used to alleviate the overfitting problems, where $r_{uic_1c_2...c_N}$ is the real and known rating given by user u on item i in context $c_1c_2..c_N$, and λ is the regularization rate used in the optimization process. By stochastic gradient descent, we are able to learn the parameters iteratively and finally achieve the best performing CAMF_CU model.

CAMF is an effective algorithm and it is able to alleviate the data sparsity to some extent. We choose CAMF_CU because we are going to explore the correlation between users and their emotional reactions, which requires a user-specific context-dependent model. The same thing can also happen to other algorithms which explore intersections or the dependency between users and contexts, such as the CSLIM_CU approach [40].

In the next section, we will introduce how to incorporate the emotional reactions as regularization terms to CAMF_CU.

4. METHODOLOGY

In this section, we introduce our methodology of how to incorporate emotional reactions into context-aware recommender systems.

4.1 Problem Statement

Recall that we assume that the different emotional reactions or expressions can be used to model users' rating behaviors. For example, assume two users gave a high rating on a same tragedy drama movie. One of them indicated his or her emotional state as "happy" when finishing the movie, because this user thought it was a really good movie. But another user may express his or her feeling as "sad" since it is a tragedy movie. The same thing may also happen to the domEmo in addition to the endEmo. The emotional reactions or expressions in this paper, refer to the different values in the dimension domEmo and/or endEmo in the LDOS-CoMoDa data.

Figure 1 presents the distribution of rating counts in each emotional state. Note that "Unknown" indicates the missing value in the LDOS-CoMoDa. We can observe that *Neutral* and *Happy* are the most two common emotional expressions in both domEmo and endEmo.

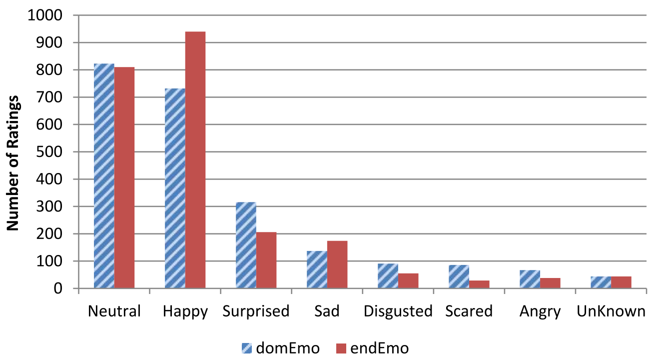


Figure 1: Distribution of Rating Counts in Each Emotional State

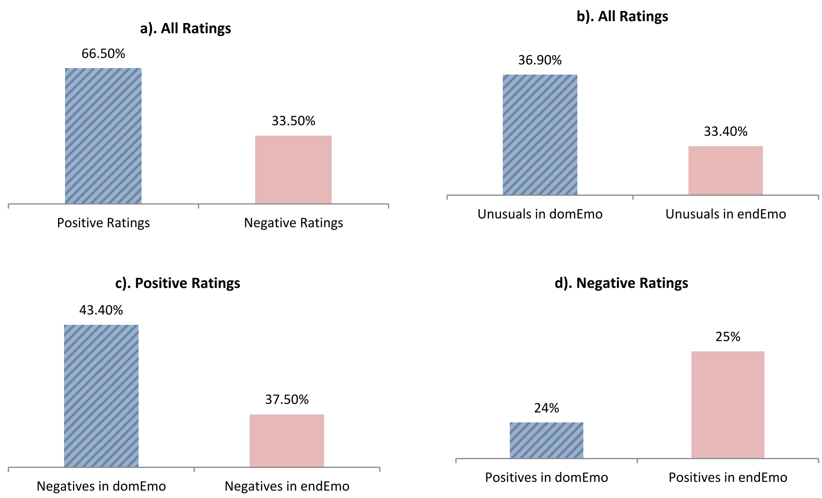


Figure 2: Distribution of Unusual Emotional Reactions in the LDOS-CoMoDa Data

Furthermore, we'd like to learn the *unusual case* to see whether users present different emotional reactions in this data. An unusual case could be two situations: 1). a user leaves a negative rating, but expresses positive emotional states in either domEmo or endEmo; 2). a user gives a positive rating while he finally indicates a negative emotion in either domEmo or endEmo.

To explore these unusual cases, we need to define which ratings and which emotions are positive or negative. In our experiments, we simply view a rating as a positive one if the rating is no less than 4; otherwise, the rating is negative. In terms of the emotional states, we only consider "Happy" and "Surprised" as positive ones, while other emotional states are negative.

A simple statistics about unusual cases in this data can be depicted by Figure 2. First of all, 66.5% of the ratings are positive ones as shown in subfigure a). Based on the subfigure b), we can observe that 36.9% of all the rating records are unusual cases (i.e., the two situations mentioned above) based on the domEmo variable, while it is 33.4% in the endEmo variable. This may tell that domEmo could be more effective and useful than endEmo in modeling users' emotional reactions.

The subfigure c) and d) further describe the two unusual situations among the positive and negative ratings respectively. In the piece of profiles with positive ratings, 43.4% of them are associated with negative emotions in domEmo – many more than the cases in endEmo. It is not surprising, since the theme or the genre of the movie will affect user's dominating emotions during the process of movie watching. For example, users may feel horrible or scared when watching a horrible movie, but finally leave a positive rating since it is a good movie. On the other hand, in terms of the records with negative ratings, there are no significant differences for the unusual cases between domEmo (24%) and endEmo (25%) based on the observations subfigure d). Recall that, there are many more positive ratings than the negative ones in this data. Therefore, it seems that users may express more unusual emotional reactions in domEmo rather than in endEmo. We suspect that the emotional reactions in domEmo may leave more influential impact on our proposed recommendation models.

The underlying assumption in our proposed approach is that user's emotional reactions or expressions on the future emotional states (e.g., domEmo and/or endEmo) can be used to improve recommendations, since they may indicate similar user tastes even if the emotional reactions are different or even opposed. The research problem can be summarized as how to incorporate these emotional reactions into existing recommendation algorithms. More specifically, we want to explore the approach to incorporate them into the CAMF approach. There are three questions we are particularly interested in:

- How to fuse this emotional reactions into CAMF?
- Does it work by providing improvements?
- Which emotional reaction is more effective? The reactions based on domEmo or endEmo?

4.2 Regularization by Emotional Reactions

First of all, how the user reacts on the movies in terms of emotional status is dependent with what type of movies the user is watching. In this case, we additionally use movie genre information in the LDOS-CoMoDa data and aggregated users' ratings for each movie type. A sample of the aggregated data can be shown in Table 3.

Table 3: An Example of Aggregated Rating Matrix

User	Genre	Rating	Time	domEmo	endEmo
U1	Action	5	Weekday	Sad	Happy
U1	Drama	3	Weekend	Sad	Sad
U2	Cartoon	3	Weekday	Happy	Angry
U2	Drama	3	Weekday	Angry	Happy
U3	Action	2	Weekend	Sad	Sad

In Table 3, we replace the column of item by movie genre to construct a new rating matrix. We will use the same 7 contextual dimensions introduced previously. Note that in the LDOS-CoMoDa data we do not know what the movie genre is, since the genre was encoded as numbers in this data.

Afterwards, we can fuse an emotional dimension (either endEmo or domEmo) into the user dimension to create a two-dimensional rating matrix. Let's take the domEmo for example, the converted rating matrix can be described by Table 4.

Specifically, we fuse the values in domEmo into the user column to create new users. The new user is represented by a combination of original user ID and value in the domEmo, and we name those new users as *emotional users*. Meanwhile, we eliminate the other

Table 4: Converted Two-Dimensional Rating Matrix

User, domEmo	Genre	Rating
U1, Sad	Action	5
U1, Sad	Drama	3
U2, Happy	Cartoon	3
U2, Angry	Drama	3
U3, Sad	Action	2

contextual dimensions from the rating matrix. In this case, we can build a matrix factorization model based on this converted two-dimensional rating matrix. And then we are able to calculate the similarity between emotional users based on the cosine similarity of each two vectors which represent emotional users. For example, we can measure how similar the "U1, Sad" to "U2, Angry" based on their co-ratings on the movies with the same genre information.

Theoretically, we can use the item information (e.g., item ID) instead of the movie genre in the rating matrix, but it will increase data sparsity. We use movie genre information only for two reasons: On one hand, using movie genre is based on our assumptions that users' different emotional reactions depend on the movie genre and user's emotional reactions, for example, user may express as happy or sad on a tragedy movie. On the other hand, it is able to alleviate the rating sparsity in the converted two-dimensional rating matrix so that we can obtain more reliable user similarities. We have tried to use item ID, but emotional users have very few co-ratings on the items, which results in worse recommendation performance compared with that when we use genre information only. Note that we use domEmo as an example in Table 4, while we can also have the same process based on the variable endEmo.

In short, the emotional users should be similar if they have similar ratings on the movies with same genre information, even if the original users have different emotional reactions on domEmo or endEmo. For example, the ratings given by "U1, Sad" and "U2, Angry" are all 3-star on the drama movies shown in the Table 4. Therefore, U1 with dominating emotion as "Sad" may share similar user tastes with U2 with dominating emotion as "Angry" to some extent.

Accordingly, we are able to create a regularization term based on the similarity of contextual users. The new loss function can be shown as Equation 4, where β is the regularization rate for the new regularization terms.

$$\min_{B_*, b_*, p_*, q_*} \sum_{r \in R} \left[\begin{array}{l} \frac{1}{2} err^2 + \frac{\lambda}{2} (\sum_{j=1}^{N} B_{u,c_j}^2 + b_i^2 + ||p_u||^2 + ||q_i||^2) \\ + \frac{\beta}{2} \sum_{v, c_{m+} \in K} Sim((v, c_{m+}), (u, c_m)) \times reg\_emo \end{array} \right] \quad (4)$$

$$reg\_emo = (B_{u,c_m} - B_{v,c_{m+}})^2 \quad (5)$$

We will use the same function shown in Equation 1. In addition, we incorporate a new regularization term in Equation 4 compared with the loss function described by Equation 3.

More specifically, we use m to denote the index of an emotional variable (i.e., either domEmo or endEmo). Take domEmo for example, m indicates the position of domEmo in the list of contextual dimensions, thus c_m is used to express user's emotional state in domEmo. According, "u, c_m" is the emotional user (introduced as Table 4), and we use K to denote the top-K nearest neighbor of emotional user "u, c_m" based on the user similarity calculated based on the matrix factorization model built upon the converted two-dimensional rating matrix. Namely, "v, c_{m+}" is one of the identified top-K nearest neighbors. We use c_{m+} to denote the emotional state in domEmo, since it is not necessary to be the same value as c_m. But they should be the contextual condition in the same dimension (i.e., the m^{th} dimension).

As mentioned previously, more similar two emotion users are, their ratings on the items (with same genre) should be similar. In our CAMF_CU model, it can be derived that user's contextual rating deviations in this emotional variable (i.e., the m^{th} contextual variable) should be similar. Namely, B_{u,c_m} and $B_{v,c_{m+}}$ should be very close. We add the squared difference of these two deviations (e.g., Equation 5) as the regularization term in Equation 4.

Additionally, how close the two contextual rating deviations are should be dependent with the similarity of two emotional users. In this case, the regularization term is weighted by the similarity between two emotional users. We name this term as "*emotional regularization term*" in this paper.

Recall that our assumption is that the emotional users should be similar because two difference users have similar ratings even if their emotional reactions are different. It can also tell that the two users actually share something in common, so we assume there should also be a similarity between two users to some extent. Therefore, we are able to additionally incorporate a "*user regularization term*" to build a finer-grained recommendation model, where the loss function can be shown in Equation 6. Again, the user regularization is also weighted by the similarity between two emotional users.

$$\min_{B_*, b_*, p_*, q_*} \sum_{r \in R} \left[\begin{array}{l} \frac{1}{2} err^2 + \frac{\lambda}{2} (\sum_{j=1}^{N} B_{u,c_j}^2 + b_i^2 + ||p_u||^2 + ||q_i||^2) \\ + \frac{\beta}{2} \sum_{v, c_{m+} \in K} Sim((v, c_{m+}), (u, c_m)) \times (reg\_user + reg\_emo) \end{array} \right] \quad (6)$$

$$reg\_user = ||p_u - p_v||^2 \quad (7)$$

Based on those two different loss functions, we are able to build two new CAMF approaches by incorporating the emotional reactions as the regularization terms. We can learn the corresponding parameters based on the gradient decent accordingly. Note that the performance of the models may also depend on the number of K-nearest neighbors used in the algorithm. In our experiments, we set different values to explore the best options in these parameters.

5. EXPERIMENTS

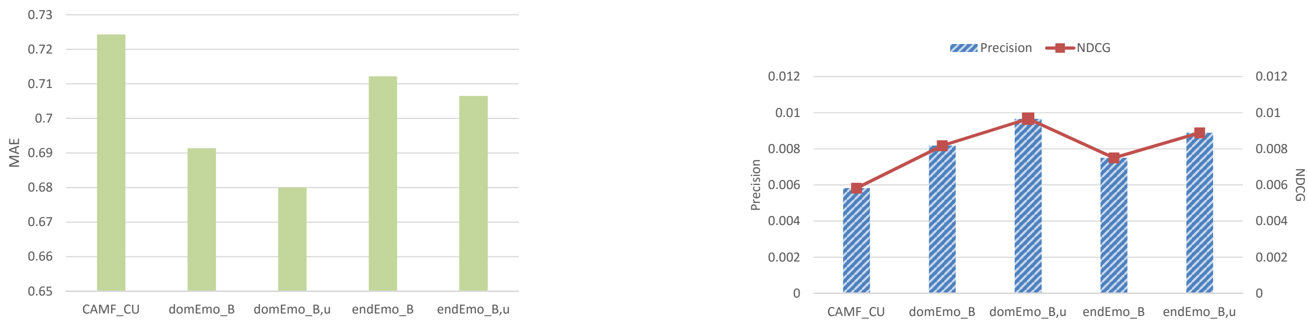
In this section, we introduce our evaluation settings and experimental results, as well as our findings.

5.1 Evaluation Protocols

We employ a 5-folds cross-validation on the LDOS-CoMoDa data set. Namely, we split the rating profiles into 5 folds and perform 5 rounds evaluations. For each round, one of the fold will be used as testing set, and the other 4 folds of data will be used as training data. We build our recommendation models based on the training set and evaluate the results according to the ground truth inferred from the testing set.

We use CAMF_CU approach as baseline, and compete its recommendation performance with the CAMF_CU models with different regularization terms. We use the CAMF_CU approach implemented in the open-source toolkit, CARSKit [41], to perform the evaluations.

More specifically, we evaluate the recommendation performance based on the rating prediction and top-10 recommendation tasks. In the rating prediction task, we use mean absolute error (MAE) as evaluation metric. We also further examine the statistical difference of MAE among different algorithms based on paired t-test at a 95% confidence level. In the top-10 recommendation, We



(a) Results on MAE

(b) Results on Top-10 Recommendation

Figure 3: Experimental Results on the Rating Prediction and Top-10 Recommendation Tasks

adopt precision as the relevance metric and Normalized Discounted Cumulative Gain (NDCG) [20] as the ranking metric. More specifically, precision is calculated as the ratio of relevant items selected to the number of items recommended (i.e., 10 in our experiment). NDCG is a measure from information retrieval, where positions are discounted logarithmically.

5.2 Experimental Results

First of all, we present our results based on the rating prediction task in Figure 3(a). We use CAMF_CU to denote the original approach without emotional or user regularization terms. Our approaches introduced in this paper are built upon CAMF_CU approach and they can be generated based on either domEmo or endEmo. We evaluate the performances by them individually. We use "domEmo_B" to represent the model using domEmo for emotional regularization, i.e., c_m denotes the emotional state in domEmo in Equations 4. By contrast, "domEmo_B, u" is used to denote the finer-grained model described in Equation 6 which contains both emotional and user regularization terms. Accordingly, "endEmo_B" and "endEmo_B, u" are the two recommendation models by using endEmo to generate the regularization terms.

Based on the results shown in Figure 3(a), our proposed approaches only using the emotional regularization term can help obtain lower MAE. All of these improvements are statistically significant based on the paired t-test. When we try to use both emotional and user regularization terms, it is able to further improve prediction accuracies. However, the improvement by endEmo_B,u fails the paired t-test compared with the endEmo_B approach. The best performing model in the rating prediction task is domEmo_B,u, where we apply emotional and user regularization terms at the same time, and these regularization terms are generated based on the emotional reactions by domEmo.

We show the top-10 recommendation results based on precision and NDCG in Figure 3(b). The bars present results based on precision at top-10 recommendation, the curve tells the results in NDCG. We can observe similar patterns shown in the rating prediction task: first, we see that the CAMF_CU models with our regularization terms are able to outperform the original CAMF_CU approach in both precision and NDCG. This finding confirms that incorporating emotional regularization terms inferred from users' emotional reactions is helpful to improve performance of context-aware recommendation.

Furthermore, we can observe the finer-grained model with additional user regularization term contributes to obtain more improvements. For example, domEmo_B,u works better than domEmo_B (19.6% improvement on precision, and 18.2% on NDCG), and endEmo_B, u outperforms endEmo_B (30.1% improvement on precision, and 18.5% on NDCG).

As mentioned before, the number of selected neighbors in our models may impact the recommendation performance. We present the impact by the number of neighbors in the finer-grained CAMF_CU approaches with two regularization terms, as shown by the Figure 4. Simply, we vary the number of neighbors from 10 to 80 with an increment of 10 on each step. The best number of neighbors should be around 40 to 50 in this data set. It is essential to examine different number of neighbors to find out the optimal selection for each recommendation model.

Finally, the experimental results help us identify that the domEmo is more useful and effective to be adopted than using endEmo. This finding is consistent with our previous analysis on the unusual cases shown in Figure 2. It makes sense since the emotional status during the process of movie watching may be very different than their emotions at the end. For example, a user may feel horrible if he or she is watching an adventure movie, but finally he or she might feel happy since it is a good movie.

5.3 Discussions

Why emotional reactions or expressions can be reused to improve the recommendation performance? As we mentioned before, one of the potential reasons is that the different emotional reactions are caused by the traits in different user personalities – users may express their emotional states or reactions in different ways. It has been well studied that the emotional expression has strong correlations with user personality, especially in the areas of psychology and social science. For example, the correlation between emotional expression and personality can be used to assist health care [13]. Harker, et al. [17] found that individual differences in positive emotional express were linked to personality stability and development across adulthood. However, there are no applications of using personality inferred from emotional reactions or expressions to further serve real-world applications, such as recommender systems. In this paper, we make our attempts to explore the impacts of emotional reactions or expressions in the recommender systems, especially in the context-aware personalization.

6. CONCLUSIONS AND FUTURE WORK

In this paper, we believe that users may place similar ratings even if they may have different emotional reactions or expressions. We propose to incorporate the corresponding regularization terms in the CAMF_CU approach to assist context-aware recommendation. Our findings based on the experimental results over the LDOS-CoMoDa movie data demonstrate that modeling user's emotional

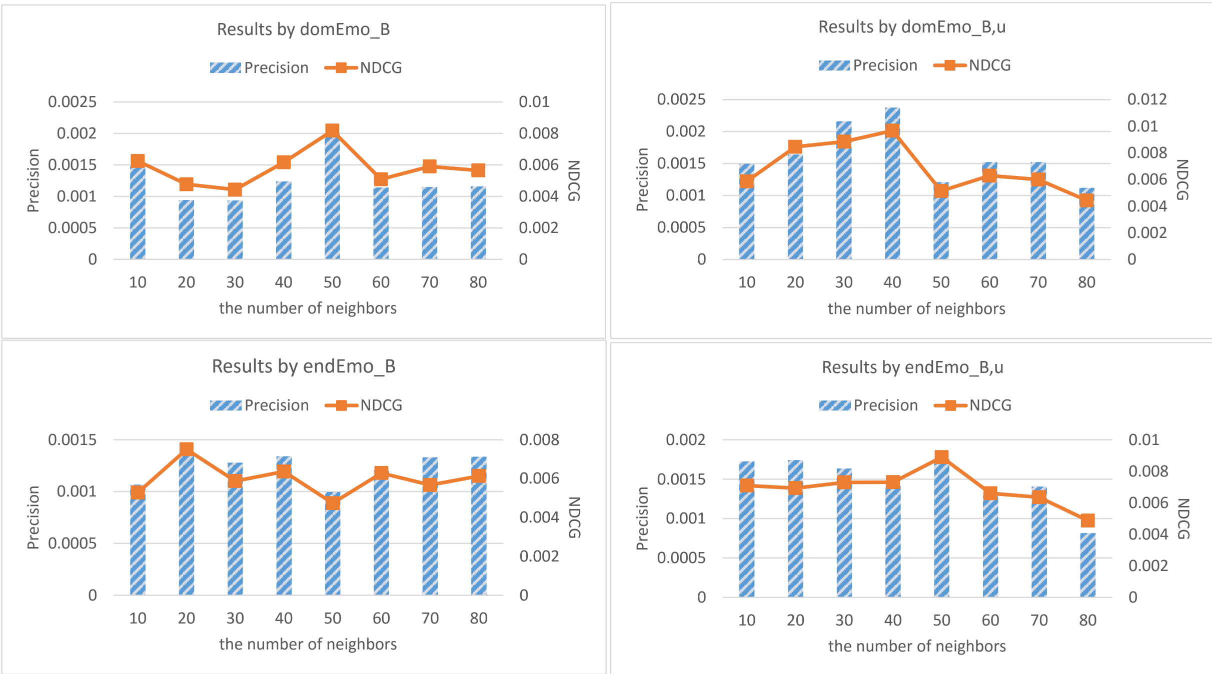


Figure 4: Impact by the Number of Neighbors

reactions is helpful to improve recommendation performance. The results also reveal that domEmo is better than endEmo to generate the regularization terms in this data set. And the finer-grained model by additionally incorporating user regularization is able to offer further improvements.

One of our future work is to incorporate these regularization terms based on different emotional reactions to more context-aware recommendation models. It is interesting to examine the similar approach in the similarity-based context-aware recommendation algorithms [43, 42] so that we can learn the similarities of not only the emotional users but also the emotion themsevles. We will also try to explore the effect of emotional reactions in other applications (such as music) rather than the movie domain.

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