Affective Prediction By Collaborative Chains In Movie Recommendation

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ABSTRACT

Recommender systems have been successfully applied to alleviate the information overload and assist user's decision makings. Emotional states have been demonstrated as effective factors in recommender systems. However, how to collect or predict a user's emotional state becomes one of the challenges to build affective recommender systems. In this paper, we explore and compare different solutions to predict emotions to be applied in the recommendation process. More specifically, we propose an approach named as collaborative chains. It predicts emotional states in a collaborative way and additionally takes correlations among emotions into consideration. Our experimental results based on a movie rating data demonstrate the effectiveness of affective prediction by collaborative chains in movie recommendations.

CCS CONCEPTS

• **Information systems → Recommender systems**;

KEYWORDS

emotion, affective computing, context-aware, recommender systems, collaborative chains

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1 INTRODUCTION

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, a user's 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*. The restaurant that a user is going to select may be different if he or she is going to have a *quick lunch alone* or a *formal dinner* with *a group of people*. Existing research have demonstrated the effectiveness of CARS and CARS have been successfully applied in multiple applications, such as movies [12, 13, 32], music [3, 4], tourism [6, 11, 28], restaurant [14, 15], etc.

Users' emotional states are one of the dynamic variables which can be viewed as context. They have been demonstrated as effective and influential contexts in recent research [13, 17, 19, 24, 30, 32]. Tkalcic, et al. [19] believes that emotions can play important roles in three stages during the user interactions with the system: entry stage, consumption stage and the exit stage, as described by Figure 1. Take movie watching for example, a user's emotion states before watching the movie, during movie watching and after the movie playing may become influential context information in the recommendation process. Research [13, 24, 32] have built effective recommendation models by incorporating the emotional states that were collected from these three stages.

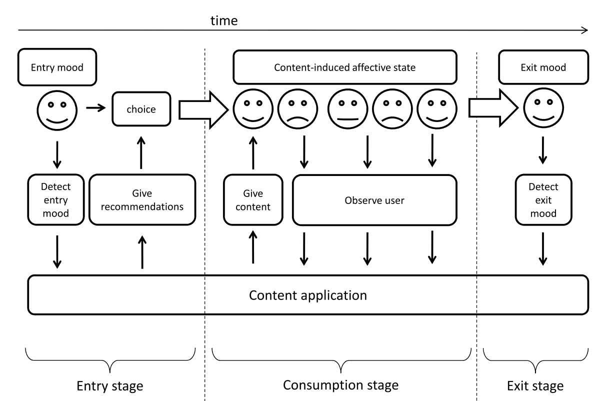

Figure 1: Three stages where emotions may take effect during user interactions with the system [19]

A user's emotional state may change overtime, not to mention during the period of the user interactions with the system. Due to the difficulty of collecting emotional states, emotion recognition and emotion prediction become two major solutions in affective computing. The task of emotion recognition [7] refers to identify or extract emotional states from different signals, such as sensors, texts, music features, etc. By contrast, emotion prediction [2] focuses more on the supervised or semi-supervised learning process to predict the emotion states from the existing knowledge.

Previous research [13, 24, 32] successfully exploit how to utilize emotions as contexts in the recommender systems, but they ignore

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the challenge of affective predictions. In this paper, we focus on the emotion predictions that can be used to predict a user's emotional stages in the consumption and exit stages. More specifically, we first explore the general approaches (such as supervised classifications) to predict emotions in the recommender systems. And we propose a novel approach named as collaborative chains to better personalize the emotional predictions. We further examine the proposed approach based on a movie data that was collected from user surveys.

2 RELATED WORK

In this section, we discuss existing work related to context-aware recommendation and emotion recognition or predictions. We also introduce the movie rating data that is used in this paper.

2.1 Context-aware Recommendation

Traditional recommendation problem can be modeled as a two-dimensional (2D) prediction – R: Users × Items → Ratings, while CARS try to additionally take context information (e.g., time, location, companion, emotions, etc) to estimate user preferences using a "multidimensional" rating function, R: Users × Items × Contexts → Ratings [1]. For example, CARS may recommend appropriate movies to us by taking *When* (e.g., weekend or weekday), *Where* (e.g., at home or at cinema) and *with Whom* (e.g., parent, kids, partner) and the user's emotional states into account.

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* [8]". In CARS, we view the dynamic attributes as the observed contexts which may change when the user performs the same activity repeatedly [23]. For example, the time, location, companion may change every time when a user is going to watch a movie. Apparently, emotion is one of these dynamic variables that can be viewed as contexts, since it may change overtime, especially during the user interactions with the system or application. Emotional state has been demonstrated as useful context information, and several research [13, 17, 19, 24, 32] have developed more effective recommendation models by considering emotions as contexts.

2.2 Emotion Recognition and Prediction

However, it is well-known that it could be difficult to collect user's emotional states. There are usually three ways to solve this problem:

- First of all, researchers try to recognize emotions from different resources. For example, we can utilize sensors to detect emotions [10]; or, we can infer emotions from facial expressions [20]; also, we may learn and predict emotions from textual information [2] or music features [18]. However, these approaches usually require either external equipment (such as sensors) or high-quality resources (such as text, facial images, or music features).
- Another way is to collect emotions explicitly. For example, emotional states can be collected from user studies [12]. Or, some applications, such as Facebook [1], encourage their users to utilize Emoji in their daily status. MoviePilot [2] tries to encourage their clients to assign emotional tags to their preferred movies. However, it requires additional human effort, or it may take a long time to acquire rich information about user's emotional states. Another challenge is that it is difficult to capture the emotional changes during the user interactions.
- Alternatively, a better way may be emotion prediction. More specifically, we can collect a sample of user's emotional states from user studies, and build learning models to predict a user's emotion. Note, this approach is different from the emotion recognition based on texts or music features. It is because the aspects of both a user and an item will be taken into account. For example, how a user will present his or her emotions after watching a given movie. In this case, personalized prediction may be required, since users' emotional reactions may be different, even if two users are given a same movie [24]. However, this approach was not fully investigated in the domain of recommender systems.

Therefore, In this paper, we focus on the third approach – affective predictions. We first explore the general approaches (such as supervised classifications) to predict emotions in the recommender systems. And we propose a novel approach named as collaborative chains to better personalize the emotional predictions. Finally, we examine the proposed approach based on a movie data that was collected from user surveys.

2.3 LDOS-CoMoDa Data Set

To discuss the LDOS-CoMoDa data, we'd like to introduce the terminologies in the context-aware recommender systems.

Table 1: Example: a Context-aware 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}.

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 [12] introduced below is one of the data sets that was collected from user surveys, and can be used for this type of

[1]Facebook, https://facebook.com

[2]MoviePilot, https://moviepilot.com/

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 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, Friend, Colleague, Parent, 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 users, or users were given a movie
Interaction	Nth interaction with a movie (N = 1, 2, 3, ...)

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 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 in order to build effective recommendation models. We'd like to retain the most influential context dimensions, since irrelevant ones may introduce noise in the data and further hamper the recommendation accuracy. Based on the statistical selection method introduced in [13], 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 [19]. 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.

In addition to these context variables, we also obtain user demographic information (such as age, gender, country, etc) and movie features (such as genre, direction, year of the movie, movie language, etc) in this data set.

3 PROBLEM STATEMENTS

Previous research [13, 19, 24, 32] have explored the contextual effects on the LDOS-CoMoDa movie data set. More specifically, [19] depicts the framework of affective recommender systems. Particularly, they emphasize the importance of emotional states in the entry stage, consumption stage and exit stage respectively. Odic [13] and our work [32] identify the most important contexts in this data and propose different ways to incorporate emotional states into context-aware recommender systems, while we find the three emotional variances are the most influential context information to improve the recommendation performance. Our work [24] in 2016 further exploits how to capture the affective effects inferred from a user's dynamic emotional reactions.

There is one drawback in all of the above work which utilize the LDOS-CoMoDa data – they identify the domEmo and endEmo are two influential emotional contexts and directly incorporate them into the recommendation models. Recall that the task in context-aware recommender systems is to suggest appropriate items to the users by given a list of context situations. In other words, the system is supposed to recommend movies to the users by taking time, location, mood into consideration. However, domEmo and endEmo are the two emotional states after user's selection on the movies. We give these influential variables a new name, "*interactive context*". Particularly, in the LDOS-CoMoDa data, they are the interactive emotional states.

Previous research [13, 24, 32] demonstrate how useful it is to utilize emotions to improve the recommendation models. But the challenge behind is that we are not aware user's domEmo and endEmo before a user makes the decision on which movie he or she is going to watch. We believe it is important to predict the domEmo and endEmo and it is necessary to take them into account to build the recommendation models, since existing research have demonstrated the importance of these two interactive emotional states.

In short, the interactive emotional states are useful to build effective recommendation models, but it is not possible to collect these emotions before a user starts watching a movie. Therefore, the main research problem in this paper becomes how to predict the interactive emotional states in advance, so that we can incorporate them into the recommendation models. The prediction can be viewed as process of emotion recognition or prediction, where we have introduced three solutions in section 2.2. In this paper, we focus on the third one – by using supervised or semi-supervised learning to make the predictions. More specifically, we can collect a sample of the data from user studies to let the subjects explicitly tell us their emotional states for domEmo and endEmo. But it is impractical to collect these information for all of the users. The next step is to learn these interactive emotional states from the sample data, in order to build context-aware or affective recommender systems.

4 METHODOLOGIES

As a summary, we are going to predict the domEmo and endEmo from the training set. Afterwards, we can incorporate these interactive emotional states together with other context information (such as time, location, companion, etc) into the recommendation models. Generally, we propose four solutions: Independent Emotion

Table 3: Transformed Rating Matrix

(a) Original Matrix

User	Item	Rating	domEmo	endEmo
U1	T1	3	P	Happy
U1	T2	5	N	Sad
U2	T1	2	N	Sad

(b) Transformed Matrix

User	Item	Rating	domEmo=P	domEmo=N	endEmo=Happy	endEmo=Sad
U1	T1	3	1	0	1	0
U1	T2	5	0	1	0	1
U2	T1	2	0	1	0	1

Classification (IEC), Dependent Emotional Classification (DEC), Independent Collaborative Prediction (ICP), Dependent Collaborative Chains (DCC).

In this section, we will introduce the four solutions to predict the interactive emotional states. After that, we briefly introduce how to utilize the predicted emotional states to produce context-aware recommendations.

4.1 Independent Emotion Classification (IEC)

Due to that the values in the domEmo and endEmo are nominal values. We can view the prediction task as a multi-class classification task. Simply, we can consider user, item, user demographic info, item features, as well as different context information (i.e., the 7 variables mentioned previously except the domEmo and endEmo) as features to predict the labels for domEmo and endEmo. We name this approach as independent emotion classification, because the process to predict domEmo and endEmo is independent. In this case, most of the classical classification algorithms can be adopted in the multi-class classification process, such as decision trees, random forest, support vector machines, and so forth.

4.2 Dependent Emotional Classification (DEC)

By contrast, the prediction process for domEmo and endEmo may be dependent. More specifically, the predicted value in one of these two emotional variables may affect the value in another variable. As shown by Figure 2, we use a classification algorithm to predict the label for one of these two emotional variables first. Afterwards, the predicted value will be considered as one additional feature to make prediction for another emotional variable.

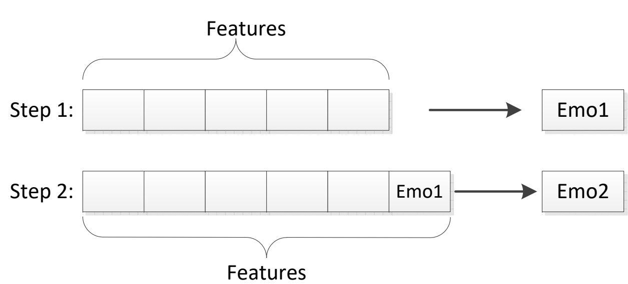

Figure 2: Workflow of the DEC Approach

This approach refers to the classification chains [16] which is a popular approach in multi-label classification [21]. It defined the workflow of the clasification process as shown in Figure 2, while any popular classification algorithms, such as decision trees, random forest and support vector machines, can be applied on top of the classification chains. Therefore, in the dependent emotional classification, we take the dependency of these two emotional variables into consideration, in comparison with the independent emotion classification approach.

4.3 Independent Collaborative Prediction (ICP)

As mentioned previously, the process of affective prediction may require personalization – given a same movie, the user's domEmo and endEmo may vary from users to users. By using classification algorithms, we can take user information into account, but the degree of personalization may be out of controls.

In this case, we try to apply classical recommendation models to predict the interactive emotional states in order to obtain better personalized results. First of all, we need to transform the original rating matrix to a new one, as shown in Table 3. Each value in the emotional states will be viewed as a single feature. The value in the new features is binary one, so that classical recommendation algorithms, such as user-based collaborative filtering, or matrix factorization can be applied to make the predictions. Note that, this approach will finally predict each interactive emotional state one by one until all of them have been predicted. If there are multiple predicted states (i.e., the predicted score is larger than zero) in an emotional variable, we will consider the emotional state with highest predicted score as the prediction for this emotional variable.

We believe the side information, including user demographic information and movie features, are useful to offer a finer-grained degree of personalization. It is because the emotional states are highly correlated with user interests and personalities. In our experiment, we utilize the one-class matrix factorization with side information [9] as the recommendation model. The loss function in the model can be described by Equation 1, where λ_1 and λ_2 are the regularization rates, and $\| \, . \, \|_F^2$ represents the Frobenius norm of a matrix.

$$\begin{aligned} L(P,Q,X,Y) = \| W \otimes (R - PQ) \|_F^2 + \lambda_1(\| U - PX \|_F^2 + \| T - YQ \|_F^2) \\ + \lambda_2(\| P \|_F^2 + \| Q \|_F^2 + \| X \|_F^2 + \| Y \|_F^2) \end{aligned} \quad (1)$$

P refers to the user matrix, while Q is the item matrix. Both the P and Q matrices are constructed by initializing N latent factors. N could be set as any number. The larger the N value is, the more learning iterations may be required to obtain the best predictive model. Therefore, P_i represents the user vector for user u_i while Qj is an item vector for item t_j. We view the binary values in different emotional states as the rating as shown in in Table 3(b). Therefore, the dot product of P_i and Q_j can be used to represent how u_i's emotional state looks like given an item t_j.

W is a binary matrix, while $W_{ij} = 1$ if the binary value in the emotional state is 1. Matrix U represents user's demographic information, and T matrix denotes the item features. In our data, the U contains the user gender and home country dimensions, while the T matrix contains the features including movie genre, the year of the movie and movie language. Matrices X and Y are latent factor matrices used to convert the matrices P and Q to the same dimension of the matrix as U and T. In this way, we are able to incorporate side information to the matrix factorization model.

The reason why it is called independent collaborative prediction is because we use the same recommendation model to predict the interactive emotional states independently and ignore the dependency.

4.4 Dependent Collaborative Chains (DCC)

Alternatively, we can adopt the collaborative predictions while we additionally take the dependency between interactive emotional states into consideration. The assumption behind is similar to the one in dependent emotional classification, as shown in Figure 2. The predicted value in one of these two emotional variables may affect the value in another variable. In this case, we use the collaborative prediction to estimate one of the two emotional variables (i.e., either endEmo or domEmo). The predicted value will be considered as additional side information to be incorporated into the one-class matrix factorization to predict another emotional state. It works like a chain, therefore we give it the name as dependent collaborative chains. Note, a similar approach, "Criteria Chains" [26], has been successfully applied in multi-criteria recommender systems to exploits the correlations among different rating criteria.

One of the challenges is how to determine the sequence in the chain. It is not a serious problem in this movie data, sine we only have two interactive emotional variables. When it comes to various interactive context variables, we need to figure out a way to produce the optimal sequence in the chain. One of the potential solution is to utilize feature selection techniques or metrics (such as information gain, Gini index, etc) to determine the sequence of variables in the chain. Information gain has been identified as an effective way to produce the sequence of chains in Criteria Chains [26].

4.5 Affective Context-aware Recommendations

After the affective prediction process, we can continue to use the existing affective recommendation models [13, 19, 24, 32] to provide context-aware movie recommendations. In this paper, we continue to use our model introduced in [24] which can be briefly introduced as follows.

Basically, the model used to produce context-aware recommendation is the context-aware matrix factorization [5]. More specifically, the rating prediction function by CAMF_CU can be described by Equation below.

$$\hat{r}_{uic_1c_2\ldots c_N} = \mu + \sum_{j=1}^{N} B_{u,c_j} + b_i + p_u^T q_i \tag{2}$$

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. $\hat{r}_{uic_1c_2\ldots c_N}$ 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.

We utilize the predicted interactive emotional states in the rating prediction above. Meantime, we also incorporate these emotional states into the loss function to further improve the recommendation model. The loss function can be described by Equations 3-6.

$$\min_{B_*, b_*, p_*, q_*} \sum_{r \in R} \left[\begin{array}{l} \frac{1}{2} err^2 + \frac{\lambda}{2}(\sum_{j=1}^{N} B_{u,c_j}^2 + b_i^2 + ||p_u||^2 + ||q_i||^2) \\ + \frac{\beta}{2} \sum_{v, c_{m+} \in K} Sim((v, c_{m+}), (u, c_m)) \times (reg\_user + reg\_emo) \end{array} \right] \tag{3}$$

$$err = r_{uic_1c_2\ldots c_N} - \hat{r}_{uic_1c_2\ldots c_N} \tag{4}$$

$$reg\_user = ||p_u - p_v||^2 \tag{5}$$

$$reg\_emo = (B_{u,c_m} - B_{v,c_{m+}})^2 \tag{6}$$

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. Accordingly, "u, c_m" is the *emotional user* (i.e., the combination of emotional state and user ID), 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).

The loss function incorporates two regularization terms: *reg_emo* and *reg_user*. The regularization term, *reg_emo*, actually tries to utilize the affective effects inferred by emotional reactions. The idea behind is that two users may have similar tastes even if their emotional reactions denoted by domEmo or endEmo are different. By contrast, the regularization term, *reg_user* further tunes up the model by learning the similarity between two emotional users.

In terms of which emotional variable should be applied in the regularization terms, our previous work [24] suggests to use domEmo. Therefore, in this paper, we utilize domEmo to generate the regularization terms in the loss function, while both domEmo and endEmo are actually used in the rating prediction functions to produce affective context-aware item recommendations.

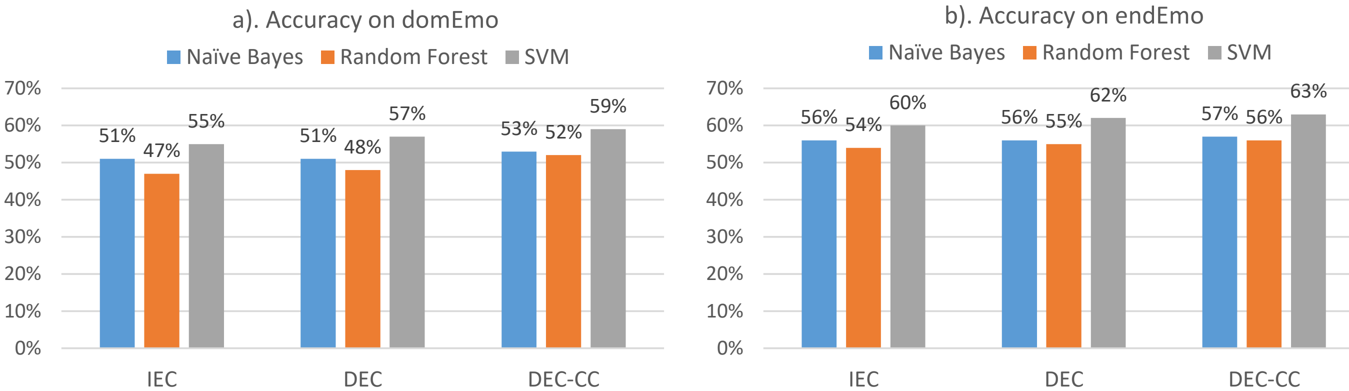

Figure 3: Accuracy of Affective Predictions by IEC and DEC

5 EXPERIMENTAL EVALUATIONS

In this section, we introduce our experimental setting and the experimental results over the LDOS-CoMoDa movie data set.

5.1 Evaluation Settings

We apply a 5-fold evaluation based on the LDOS-CoMoDa movie data set. There are two kinds of evaluations in our work: first of all, to examine how the proposed affective prediction solutions work, we use the accuracy as the metric – the percentage of correctly predicted values in the emotional states. In addition, we will take these predicted emotional states into account and reuse the recommendation model in [24] to provide context-aware movie recommendations. In terms of the evaluation on the recommendations, we perform evaluations on both rating prediction task and top-10 recommendation task. We adopt mean absolute error (MAE) and normalized discounted cumulative gain (NDCG) as the evaluation metrics respectively. Recall that we are going to perform the top-10 context-aware recommendation. The calculation of NDCG will also take contexts into consideration.

The experimental setting for each solution can be summarized as follows:

- Independent Emotion Classification: we try different classification algorithms, including Naive Bayes, support vector machine (SVM) and random forest.
- Dependent Emotional Classification: there could be two possible solutions in this category: one of them is to reuse the predicted value in one of the emotional variables as new features to proceed with the next-round multi-class classification. In this case, we reuse the classifiers mentioned above. Another way is to convert the prediction process to a multi-classification task and adopt classification chains. We tried both in our experiments.
- Independent Collaborative Prediction: we adopt the model introduced in Equation 1. Note the predicted value will be a numerical one within range [0, 1]. We need to compare which one is the largest to make a decision which value should be viewed as the prediction for a single emotional variable. For example, there are seven values in endEmo. The value with largest predicted value will be considered as the predicted endEmo state.
- Dependent Collaborative Chains: we reuse the recommendation model in Equation 1, but we take correlations of emotional states into consideration by the collaborative chains as introduced in section 4.4.

5.2 Results and Findings

First of all, we compare the accuracy of affective predictions by IEC and DEC. The results can be shown by Figure 3.

We use IEC and DEC to represent the independent and dependent emotional classification respectively, while "DEC-CC" denotes the DEC solution by using classifier chains. Based on the results shown in Figure 3, we can observe that SVM is the best classifier for all of these three solutions. By incorporating the dependency into the classification, DEC and DEC-CC actually can improve the prediction accuracy by at least 1%. By using SVM, DEC-CC performs the best and it is able to improve the accuracy of IEC solution by 3%. However, the highest accuracy is only 59% for domEmo and 63% for endEmo among all of the IEC and DEC solutions.

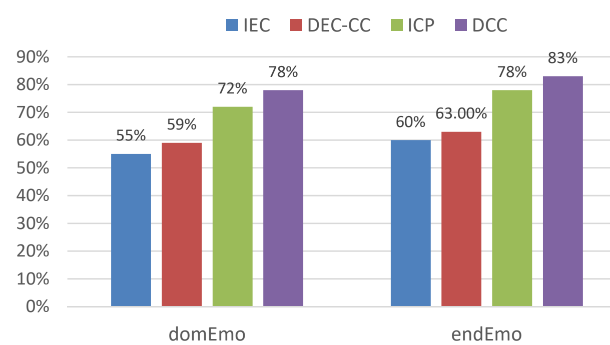

Figure 4: Accuracy of Affective Predictions by IEC, DEC-CC, ICP and DCC

Figure 4 depicts the comparison of accuracy by the independent collaborative prediction (ICP) and the dependent collaborative chains (DCC) with the best performing IEC and DEC-CC results.

Generally, we can find that ICP is able to improve the accuracy by at least 10%, while DCC is able to further offer a 4% improvement. It is not surprising since we expect ICP and DCC can improve the degree of personalization by using the recommendation model for affective predictions.

Table 4: Performance of Context-aware Recommendations

	MAE		NDCG	
	Actual	**Predicted**	**Actual**	**Predicted**
domEmo	0.68	0.684	0.0092	0.0087
endEmo	0.708	0.709	0.0085	0.0085
Full Model	0.68	0.684	0.0094	0.0090

Finally, we incorporate these predicted interactive emotional states into the context-aware recommendation model described in [24]. More specifically, we incorporate domEmo and endEmo as regularization terms, and apply an additional user-specific regularization in the recommendation model. For more details, refer to our work [24] or Section 4.5.

The results can be presented in Table 4. domEmo represents the context-aware recommendation model that we use domEmo as emotional regularization plus a user regularization only. endEmo denotes the model that we apply endEmo as emotional regularization plus a user regularization, while the "Full Model" refers to the model by using both domEmo and endEmo as the emotional regularization terms.

We compare the model performance by using the actual knowledge about the emotional states in the domEmo and endEmo variables and using the predicted emotional states by the DCC solution as shown above. In terms of the performance in MAE, we can observe there are no significant difference by using the actual and predicted emotional states. The comparison actually fails the paired t-test at 95% confidence level. By contrast, the NDCG value is generally decreased if we use the predicted emotional state. Recall that the highest accuracy in the affective prediction by the DCC solution is 78% in the domEmo and 83% in the endEmo. However, the NDCG values are still acceptable. We expect a better results if we can find better models to predict the interactive emotional states.

6 CONCLUSIONS

In this paper, we propose to predict the interactive emotional states by a supervised learning process. More specifically, we introduce and discuss four solutions: independent emotional classification, dependent emotional classification, independent collaborative prediction and dependent collaborative chains. We perform empirical evaluations of these four solutions over a movie data set. We find that incorporating dependency among emotions is able to improve the prediction accuracy, and the collaborative chains finally work the best among the solutions. The context-aware recommendation performance can still be acceptance after we take the predicted emotional states into the recommendation model.

In our future work, we expect to evaluate the proposed four solutions on data sets with emotional states in other domains. Also, we are going to seek advanced approaches to improve the accuracy of emotion predictions. Due to the fact that emotional states can be considered as contexts, the task of emotion predictions can be solved by the approaches for context predictions or suggestions [22, 25, 27, 29, 31]. We plan to reuse the approaches in context suggestion to further improve the quality of affective predictions.

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