A Study of Learner-Oriented Negative Emotion Compensation in E-learning

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(Submitted May 14, 2013; Revised December 29, 2013; Accepted March 10, 2014)

ABSTRACT

E-learning provides an unprecedented flexibility and convenience for e-learners by breaking the limitations of space and time. However, the role of emotion is neglected in current e-learning systems. We focus strictly on negative emotions of e-learners, integrating emotion regulation theories with recommender technique, and present the study of learner-oriented negative emotion compensation in this paper. Inspiring from the existing emotion regulation model in the field of psychology, we design the architecture of learner-oriented negative emotion compensation in e-learning. Finding e-learner’s personalized emotion regulation strategies and methods from questionnaires, we propose an approach of e-learner’s negative emotion compensation based on recommender users and music. In practice, the usability of emotion compensation is verified by an e-learning platform, as a complementary demonstration, the learner satisfaction is done by a 90-e-learner survey in real e-learning. The results show that the proposed learner-oriented negative emotion compensation provides greater satisfaction for the e-learner, and is a feasible and effective method for e-learner to decrease negative emotions in e-learning.

Keywords

E-learning, Emotion compensation, Learner-centered design, Recommender system

Introduction

Emotion plays a significant role in the cognitive process of humankind. Neurobiology addresses the emotional basis of our full repertoire of cognitive options, including learning, attention, memory, and social functioning, all of which involve emotional process (Afzal & Robinson, 2010). Psychology also demonstrates that emotion is significantly related to students’ motivation, learning strategies, cognitive resources, self-regulation, and academic achievement (Pekrun et al., 2002). Empathy with the learner’s emotion would increase their motivation in learning (Pérez-Marin & Pascual-Nieto, 2012). All findings indicate that the formation of a complex cognitive system is usually accompanied by emotions.

Emotions of the user are usually classified into three categories: positive, neutral and negative. As a double-edged sword, emotions possess the dual use of either hindrance or help. Negative emotions turn an easy task into a difficult one to perform, while positive emotions lead to an easier task performance. When negative emotions are too strong, performance is inhibited (John & Gross, 2004). In learning systems as well, optimal emotions can enhance enthusiasm for learning, but negative emotions suppress learners’ interest.

E-learning provides an unprecedented flexibility and convenience for learners by breaking the limitations of space-time. While most researchers are concerned about the learners’ cognitive process, they neglect the emotional role in current e-learning systems. The interactions of e-learners and teacher-learner rely on keyboard and mouse, both of which are "blind" (the visual function), "dumb" (the language capability), and "deaf" (the auditory function), without the least emotion. The e-learners can hardly feel emotional stimulation and in e-learning process, so boredom arises and learning interest and learning efficiency are diminished. The inadequacy of affect is provoking great e-emotional interaction concern in recent years, and negative emotion compensation has emerged in the e-learning domain.

Specifically, focusing on negative emotions of e-learners in typical e-learning situations, we present the study that an effective approach is proposed to decrease e-learners’ negative emotions. The remainder of this paper is organized as follows. We introduce related work in Section 2. Next, after analyzing e-learners’ interactions in four modes of delivery, we propose the architecture of learner-oriented negative emotion compensation in e-learning, and describe...
it in detail. Section 4 presents a prototype to check proposed approach’s feasibility and a 90-e-learner survey to check e-learner’s satisfaction on negative emotion compensation in e-learning. Finally, Section 5 discusses and concludes the paper.

**Related work**

Technology is used to implement different pedagogies, whether based on prevailing psychological conceptions, novel psychological explanations, or pedagogical justifications. They are tightly coupled and reciprocal (Salomon & Almog, 1998). In this section, we introduce the psychological concepts, including the definition and model of emotion regulation, and apply them for negative emotion compensation in e-learning.

Most research on emotion regulation has been done in the field of psychology, where psychologists have argued the definition of emotion regulation in much of literatures. Thompson (1994) states: “Emotion regulation consists of the extrinsic and intrinsic processes responsible for monitoring, evaluating, and modifying emotion reactions, especially their intensive and temporal features, to accomplish one’s goals.” He emphasizes that setting goals and taking the best opportunities are very important in emotion regulation. Gross (2001) describes: “Emotion regulation includes all of the conscious and non-conscious strategies we use to increase, maintain, or decrease one or more components of an emotional response.” Individuals may have different emotion regulation strategies and methods. Larsen (2000) proposes that in mood regulation the emphasis is more on mood per se, on altering the ongoing affective state without much reference to objective life events. Emotion regulation may be conceptualized as consisting of a series of distinct but interrelated control processes. The model is an application of a general cybernetic model involving feedback of negative emotion regulation.

The applications of emotions grew to cover a rage of techniques in learning. REP (Reengineering Educational Pedagogy based on conceptualizing the impact of emotions upon learning) is the MIT research project that aims to establish an executable learning partner which can track the learners’ emotion state in learning process (Kort et al., 2001). The REP model depends on Plutchik & Ekman's basic expression to establish an emotion model for learners in the learning process. Based on the REP model, the integration of characteristics and goals determines the learners’ emotion state (Shen et al., 2009). In computer adaptive tests, adaptive feedback of emotions is characterized by negative emotions to describe emotional behaviors (Economides, 2006). A negative anxiety-frustration loop dominates learner’s emotions, making it necessary to break the negative loop by means of psychological theories and technology (Juutinen & Saariluoma, 2012). Research results help us to know the fundamental characteristics of learners’ emotion regulation, and inspire us to design an appropriate architecture of negative emotion compensation for e-learners.

**The architecture of negative emotion compensation**

Breaking down the e-learners’ behavior into the four modes of delivery (i.e., real-time classroom, group discussion, courseware on demand and questioning-answering), and inspiring from the existing emotion regulation model (Larsen, 2000; Gross, 2001) in psychology domain, we define the architecture of learner-oriented negative emotion compensation in e-learning. The architecture consists of three modules: emotion recognition, personalized emotion regulation and negative emotion compensation, and is shown in Figure 1. First, we recognize e-learner’s current emotion state. If an e-learner has some optimal emotions (or neutral calmness), she go on with her study in e-learning. Otherwise, she is redirected to the personalized emotion regulation module. Then the compensation list (music and user) is presented to the e-learner based on her historical compensation cases until the e-learner’s negative emotion is alleviated to pursue her study.

The detailed analysis of the learner-oriented negative emotion compensation is demonstrated in following section. In general, there are four modes of delivery in e-learning: real-time classroom, group discussion, courseware on demand and questioning-answering. The real-time classroom resembles the real physical classroom in that it can elicit learners’ emotions. Group discussion presents the usual learner-to-learner interaction pattern similar to a chat room, where users’ communication mainly depends on interactive text. And almost all of the information exchange between e-teachers and e-learners are lost in courseware on demand. Finally, Q&A, similar to the BBS, also relies on interactive text, either online or off-line. The interaction patterns of these can be classified into synchronous
interaction and asynchronous interaction. The former includes real-time classroom, group discussion and online Q&A, and the latter contains courseware on demand and off-line Q&A.

![Figure 1. Learner-oriented architecture of emotion compensation](image)

The emotion recognition is regarded as the prerequisite of the negative emotion compensation. E-learners’ emotions are recognized by multimodal communication, including facial expression, speech, body language, behaviors and interactive text. The recognition from facial expression (Gnjatovic & Rosner, 2010), speech (Pantic & Rothkrantz, 2000) and body language (Schindler et al., 2008) requires learner to be equipped with some detection devices, such as wearable sensors and high resolution cameras. However, in real scenarios, e-teacher often face with thousands of online e-learners, it is almost impossible for each e-learner to be equipped with expensive video and audio analysis devices with the limitations of costs and network bandwidth, especially for the schools or families in developing countries, such as China (Tian et al., 2009). So, we emphasize the emotion recognition from interactive text and behaviors from the e-learners’ logs in asynchronous interaction in this study.

**Current emotion recognition**

*Interactive text*

Interactive text is the most popular communication means in modes of delivery, such as group discussion, courseware on demand and questioning-answering. Because the interactive text is composed of some sentences, the emotion recognition from interaction text depends on the analysis of sentences’ sentiment. Between the syntactical rules and affective lexicon are the fundamental factors in the analysis of sentences’ sentiment at interactive text. Supposed the sentence is a compound sentence, conjunction should be concerned. If it is successive (e.g., and, or, and so etc.), the resulting vector is the maximum intensity in vectors of both clauses; if it is adversative (e.g., but,), the resulting vector is following after the connectors clause (Neviarouskaya et al., 2007). Or else, this sentence is simple sentence. Following, the word device is used to selected emotion words from a simple sentence (or a clause).

For each emotion word, its affective feathers are described by a vector $e = (\lambda_1, \lambda_2, ..., \lambda_n)$, $n$ is the category of basic emotions. Variable $\lambda$ is the set of intensities corresponding with basic emotions. If $\lambda_i$ represents the intensity of positive basic emotion, $\lambda_i$ is from 0 to 1, ibid, if $\lambda_i$ represents the intensity of negative basic emotion, $\lambda_i$ is from -1 to 0. The sentiment of sentence is expressed by equation (1), here $m$ refers to the number of emotion words, according to different modifier (e.g., very, extremely and most etc) and prefixes (e.g. un and non), $\sigma$ is the weighted value.
\[ E = \sum_{j=1}^{m} e_j \]

When \( E \) is equal to zero denotes that the emotional value of sentence is zero, the learner’s current emotion is calmness; When \( E \) is greater than zero means that the emotional value of sentence is positive number, the learner’s current emotion is the positive; On the contrary \( E \) is negative number, the e-learner’s current mood is negative. Of all these three emotional states of e-learner, negative emotions should be regulated in the study.

Behavior in courseware on demand

The e-learner’s behaviors in courseware on demand come from the log of Internet Education School of Xi’an Jiaotong University (http://www.dlc.xjtu.edu.cn/) from May 2010 to September 2012. The number of CoD (Course on Demand) in a day is illuminated in Figure 2. It can be seen that the e-learners’ demand for CoD varies greatly. The playing time of network educational resource files is about 49 minutes, supposing that the unit time interval is three minutes, the possible distribution of the cumulative probability of stop-on-demand in a file of CoD is described by Figure 3, the transverse coordinates indicate the length of playing time, and longitudinal coordinates show the cumulative probability of stop-on-demand. Thus from the above in-depth analysis, we arrive at the following views: when e-learners demand the courseware, they wait too long on courseware due to the limitations of service and network. As a result, e-learners lose patience and stop on demand; when e-learners roughly understand the content of the courseware, after watching for a few minutes, the content of the courseware causes e-learners to lose interest in learning; for popular courseware, e-learners may have a herd mentality leading to more e-learner requests on-demand. When e-learners start a video which is not the desired courseware, they stop playing.
Personalized regulative strategy of emotion

Emotion regulative strategy not only provides powerful theoretic instruction for emotion compensation, but also acts as a bridge between recognition and compensation. It is a key element of the learner-oriented architecture of emotion compensation. Because individuals have difference in personality traits, they may use different emotion regulative strategies in e-learning. Integrated emotion regulative strategies with the personality of e-learners, the corresponding emotion regulative methods of e-learners are determined.

Questionnaire is often used to construct and verify theories in the domain of pedagogy and psychology (Gross, 2001). We intend to use three questionnaires (the Big Five Questionnaire, ERQ and NMR-S) to acquire e-learners attributes including personality, emotion regulation strategy and emotion regulative method and construct the matching rule base for emotion compensation.

In the present study, the Chinese version of questionnaires (ERQ and the Big Five) are developed with a back-translation procedure and used to measure emotion recognition strategy and personality of participants. One bilingual Chinese-English person translated the English version of the ERQ and the Big Five into Chinese. Discrepancies emerging from this back-translation were discussed and adjustments to the Chinese translation of the ERQ and the Big Five were made.

The Big Five depends on a rapid detection version by Shafer (1999), which is a 30-item short form and consist of five dimensions, neuroticism (N), extraversion (E), openness (O), Agreeableness (A) and conscientiousness (C), each dimension contains six items which are a pair of bipolar adjectives. And ERQ is a 10-item questionnaire, which is designed to assess individual differences in the habitual use of two emotion regulation strategies: cognitive reappraisal and expressive suppression. Emotion regulation strategies (reappraisal and suppression) questionnaire which is comprised of 10 items, six items of them are used to appraise the cognitive reappraisal, the others are used to appraise the suppression expression. The items are rated on a 7-point scale ranging from 1 to 7, with 1 being strongly disagree and 7 being strongly agreed. The data of e-learners’ personality and emotion regulative strategy are recorded and used in negative emotion compensation module.

A 20-item questionnaire named the Negative Mood Regulative Scale which is operated under the assumption that users encounter the predicament of emotion in the e-learning process. Every given item indicates a concrete action, for example: “You would like to chat with friends?” Respondents select a value from 1 to 5 where a high value represents strong agreement, and a low value represents strong disagreement.

In order to obtain reliable data of samples, we select participants that have an experience in e-learning. A total of 60 participants are recruited through the BBS of Xian Jiaotong University in Chinese. They haven’t a history of psychopathology and neurological impairments via an open-ended format in their self-report on a demographic questionnaire. To ensure the quality of data, we give participants brief oral instructions including the importance of real data and the objective of investigation. Participants can cope with the study via paper-based questionnaires and e-questionnaires in Internet. The results show that 97% of respondents believe doing something is helpful to relieve negative emotional tension, about 95% of respondents approve of enjoying their favorite activities (e.g., music, movie) and 90% prefer chatting with friends to share their emotional predicament.

From above results, learner would like to listen to music in negative emotional state. Music loads emotional content to reduce the listener’s current emotion (Kaminskas & Ricci, 2012). Listeners can perceive and produce an emotion when music reaches their ears (Juslin & Sloboda, 2001). Listening music as a popular way can evoke powerful emotions and compensate negative emotion of e-learners.

Negative emotion compensation

Among the four modes of delivery, face-to-face interacting with teacher is done in the real-time classroom; e-teacher and peer assist e-learner to relieve negative emotion in group discussion and online Q&A; and expert’s guiding paired with music help e-learners to cope with negative emotion in CoD and off-line Q&A. As is mentioned above, we present an algorithm of negative emotion compensation to automatically recommend music and users (expert, e-teacher and peer) to alleviate e-learners’ negative emotion.
The process of negative emotion compensation

The result has proved that personality traits relate to emotion regulating (Qin et al., 2011). Extroverted personalities prefer to select cognitive reappraisal to regulate negative emotion, whereas neurotic types are always apt to select suppression of expression (Dennis, 2007). We can anticipate e-learners’ emotion reaction based on personality (Hoerger & Quirk, 2010). Moreover, several studies touching upon trust and personality traits show that people with similar personalities are more trustful (Golbeck, 2009) of one another. We associate emotion with trust and personality traits in negative emotion compensation. The process of negative emotion compensation is divided into three steps, which includes computing similarity score, predicting ratings and producing compensation list. It is illustrated in Figure 4.

![Figure 4. The process of negative emotion compensation](image)

The similarity score is used to measure the preference relation among e-learners. The larger score of the similarity means the more similar between e-learners. Several ways have been used to measure the user similarity score, such as Pearson correlation, Spearman correlation and Cosine correlation. Comparing the existing experimental result, the Pearson correlation is better than the Cosine correlation on the performance of calculating similarity score (Breese et al., 1998) by ratings. However, the Spearman correlation computes a measure of correlation between ranks instead of ratings (Herlocker et al., 2002). So the Pearson correlation is used to measure e-learner similarity on ratings. The evidence (Golbeck, 2009) shows that the higher the trust value between two users, the larger the similarity. So the rating value and the trust value jointly decide the similarity score in emotion compensation. Meanwhile, when insufficient or even no items are co-rated by e-learners, the trust value is used as the similarity score. The trust value of fresh e-learner can be evaluated by personality from the personalized emotion regulation module. The similarity score is expressed in equation (2).

\[
\omega_{u,v} = \kappa p_{u,v} + (1 - \kappa) t_{u,v}
\]  \hspace{1cm} (2)

\[
p_{u,v} = \frac{\sum_{i \in I_{u,v}} (R_{u,i} - \bar{R}_u)(R_{v,i} - \bar{R}_v)}{\sqrt{\sum_{i \in I_{u,v}} (R_{u,i} - \bar{R}_u)^2} \sqrt{\sum_{i \in I_{v,i}} (R_{v,i} - \bar{R}_v)^2}}
\]  \hspace{1cm} (3)

Where \(\omega_{u,v}\) is the similarity score between learner \(u\) and learner \(v\), \(t_{u,v}\) is the trust value between learner \(u\) and learner \(v\), \(p_{u,v}\) is the similarity score on ratings given by learner \(u\) and learner \(v\), and is calculated by expression (3). Here \(R_{u,i}\) is rating that learner \(u\) rated item \(i\) (i.e. music), \(\bar{R}_u\) is the average rating of learner \(u\), \(I_{u,v}\) are the co-rated items by learner \(u\) and learner \(v\). The rating value of unknown item is calculated by equation (4).

\[
R_{u,j} = \bar{R}_u + \frac{\sum_{v \in T_u} \omega_{u,v} \ast (R_{v,j} - \bar{R}_v)}{\sum_{v \in T_u} \omega_{u,v}}
\]  \hspace{1cm} (4)
Where $U$ is the set of learners and $j$ is an unknown item of learner $u$. The compensation list of top $n$ musical track and $m$ users are recommended to compensate negative emotion for the e-learner.

Besides, when a fresh e-learner enters emotion compensation system, she has no historical ratings and trust relations with others. To solve the fresh e-learner’s problem, we can find similar e-learners based on her personality traits and emotion regulation strategy.

**The algorithm of negative emotion compensation**

The algorithm of negative emotion compensation is presented in table 1.

**Table 1. The algorithm of negative emotion compensation**

<table>
<thead>
<tr>
<th>Steps</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Set the $u$ as the root of $T$ and $u \in U$;</td>
</tr>
<tr>
<td>2.</td>
<td>Select ratings which are rated together by $u$ and others under $e$;</td>
</tr>
<tr>
<td>3.</td>
<td>Compute the similarity score between $u$ and $v$ on the ratings;</td>
</tr>
<tr>
<td>4.</td>
<td>Compute the similarity score between $u$ and $v$ based on $\omega_{u,v} = \kappa p_{u,v} + (1-\kappa) t_{u,v}$;</td>
</tr>
<tr>
<td>5.</td>
<td>Select top $m$ neighbors of $u$ according to $t_{u,v}$;</td>
</tr>
<tr>
<td>6.</td>
<td>Run $R_{u,j} = R_u + \sum_{v \in U} \omega_{u,v} \times (R_{u,j} - R_v)$;</td>
</tr>
<tr>
<td>7.</td>
<td>Find top $n$ pieces of music;</td>
</tr>
<tr>
<td>8.</td>
<td>Return $L$.</td>
</tr>
</tbody>
</table>

**Experiments**

In order to demonstrate the performance of the algorithm of negative emotion compensation, we compared the other two learner’s preference measures respectively using the correlation on the co-ratings and the trust value on the different sparsity of the rating matrices of datasets, Epinions and EC. The correlation on the co-ratings is used to weight user’s similarity and judge the user’s preference in the collaborative filtering (CF for short), while the trust value is regard as user’s similarity in the trust-based recommendation (TR for short). The learner’s preference is judged by the learner’s similarity, which is calculated selectively using the correlation on the co-ratings and the trust value in negative emotion compensation (NEC for short). The experimental results show that NEC outperforms CF and TR, which provides a basis for implementation of emotion compensation, and learner satisfaction increases in the learner-oriented negative emotion compensation system.

**Dataset**

There are several datasets which are usually used to do experiments on a trust-based recommendation, in particular one named Epinions is extracted from the trust network datasets released at trustlet.org (Massa & Avesani, 2006), which was derived from Epinions.com by Paolo Massa and Paolo Avesani. In the dataset, the ratings follow the 1, 2, 3, 4, and 5 numerical scales, the trust value is either the value of 0 or the value of 1; obviously, the value of 0
indicates the trust relationship between user A and user B does not exist, while the value of 1 represents that user A trusts user B. There are 49,290 users and 139,738 items in the dataset from Epinions.com, where each user rated at least one item in the past. The sparsity of the rating matrices of Epinions is 99.99135%.

Because of the lack of reference data and because of the limitation of unified categories of emotions (Kaminskas & Ricci, 2012), there is no popular dataset for NEC. Following the principle that the categories of emotions are determined by the task and domain of research, we consider a scenario where we use music to regulate a learner’s negative emotions when they encounter the predicament of emotion in the e-learning process. These negative emotions figured frequently in e-learning: anxiety, anger, disgust, sadness, shame, and hopelessness (Tian et al., 2009). To illustrate and validate our work, we endeavored to set up a website to acquire data, named “EC” in our experiment. Volunteers were recruited from Xi’an Jiaotong University in China, and 102 were selected to rate music at a resource-making website. Participants did not have a history of psychopathology or neurological impairments, as self-reported via an open-ended demographic questionnaire. In this experiment, we collect 1548 pieces of music taking into account the multidimensional features of music as well as cross-cultural differences. Each piece of music is rated in different negative emotional contexts. All ratings follow the 1-extremely bad, 2-bad, 3-average, 4-good, and 5-perfect numerical scale. Participants are expected to annotate randomly selected music for eight weeks. While listening, they can click on the left rectangle to pause/play the song; drag-and-drop the middle rectangle to listen to the song again; drag-and-drop the right rectangle to adjust the volume; and click on the button to modify the annotation. Further, titles are shown on the webpage. In total, 102 participants gave 21,738 ratings. The sparsity of the rating matrices of EC is 96.663%.

**Evaluation**

In general, both accuracy and coverage are usually used to evaluate the performance of recommendation algorithm (Herlocker et al., 2004; Ruffo & Schifanella, 2009; Herlocker et al., 2002). The accuracy is measured according to Mean Absolute Error (MAE), Mean Absolute User Error (MAUE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). If \( \{p_1, p_2, \ldots, p_n\} \) refers to the predicted ratings, and \( \{r_1, r_2, \ldots, r_n\} \) is the actual rating, then the MAE, MSE and RMSE are expressed by equation (5), (6) and (7), respectively.

\[
\text{MAE} = \frac{\sum_{i \in G} |p_i - r_i|}{n} \quad (5)
\]

\[
\text{MSE} = \frac{\sum_{i \in G} (p_i - r_i)^2}{n} \quad (6)
\]

\[
\text{RMSE} = \sqrt{\frac{\sum_{i \in G} (p_i - r_i)^2}{n}} \quad (7)
\]

As mentioned above, suppose \( U \) is the set of all users and \( m \) refers to the number of users, \( h \) is the number of ratings given by \( U \), then the MAUE and \( AUE \) are expressed by equation (8) and (9).

\[
\text{MAUE} = \frac{\sum_{u \in U} AUE_u}{m} \quad (8)
\]

\[
AUE_u = \frac{\sum_{i \in u} |p_i - r_i|}{h} \quad (9)
\]

The coverage is a measure of the percentage of predictions given by the recommendation algorithm, and includes rating coverage (RC) and user coverage (UC), which are respectively denoted as equation (10) and (11).

\[
\text{Rating Coverage} = \frac{p}{s} \quad (10)
\]

\[
\text{User Coverage} = \frac{k}{m} \quad (11)
\]

where \( s \) is total number of all ratings, \( p \) is the quantity of ratings predicted, \( m \) is the total number of all learners, and \( k \) is the number of learners predicted.

Because emotion is a subjective psychological experience, self-reporting is an important evaluation tool originating from feedback in the psychological domain. We measure whether the learners consider the music recommended by NEC is best satisfying than those by CF, TR. In order to perform this evaluation of NEC, the learners’ satisfaction degree (SD for short) is proposed and expressed by equation (12).
\[ SD = \sum_{i=1}^{5} r_i \cdot \frac{i}{1 \cdot m} \]  

(12)

where \(i\) represents ratings on a scale from 1 to 5, with the higher value representing more satisfaction, \(r_i\) is the quantity of \(i\), \(l_i\) is the quantity of recommended music for one learner.

**Experimental results**

We run NEC, CF and TR on Epinions, the accuracy and coverage are shown in Figure 5 and Figure 6, respectively. It is seen that the MAE, MAUE, MSE, RMSE of NEC is lower than that of CF and higher than that of TR; the rating coverage of NEC is much higher than that of CF and TR, respectively; and the user coverage of NEC is much higher than CF and TR.

**Figure 5. The accuracy of NEC, TR, CF on Epinions**  
**Figure 6. The coverage of NEC, TR, CF on Epinions**

Next, Figure 7 indicates that NEC and CF hardly differ in the MAE, MAUE, MSE, RMSE, which both offer better accuracy than TR; and the rating coverage of NEC and TR is much higher than that of CF, even attaining 100% on user coverage in Figure 8. From the above experimental results, the NEC has better performance on datasets with different sparsity of the ratings matrix.

**Figure 7. The accuracy of NEC, TR, CF on Epinions**  
**Figure 8. The coverage of NEC, TR, CF on Epinions**

Furthermore, Table 2 illustrates the result of learners’ subjective evaluation under an emotional context of anxiety: NEC gains the better satisfaction of recommendation. In a word, NEC shows better performance on learner’s satisfaction.

**Table 2. Learner’s satisfaction degree of CF, TR and NEC in anxiety**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>The number of ratings</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>CF</td>
<td>1</td>
<td>1</td>
<td>9</td>
<td>27</td>
<td>46</td>
<td>9</td>
<td>3.656</td>
</tr>
<tr>
<td>TR</td>
<td>1</td>
<td>1</td>
<td>9</td>
<td>28</td>
<td>35</td>
<td>17</td>
<td>3.644</td>
</tr>
<tr>
<td>NEC</td>
<td>1</td>
<td>1</td>
<td>8</td>
<td>29</td>
<td>35</td>
<td>17</td>
<td>3.656</td>
</tr>
</tbody>
</table>
Visualization of negative emotion compensation

The emotion compensation system as a prototype has been designed to verify the availability of the architecture of negative emotion compensation. And the mirror of learner’s satisfaction of negative emotion compensation is reported through the system.

When a fresh e-learner logs in emotion compensation system, she would complete three questionnaires (Big Five, ERQ and NMR-S). Following, if the e-learner encounters difficulties in e-learning process, she may raise negative emotion that is recognized immediately. Then the system auto-recommends appropriate music and users (peer, teacher and expert) to the e-learner based on trust and historical compensation data. For example, suppose an e-learner is talking about the topic of final examination of College English, when “I’m very anxious” appeared in interactive text, the sentence is analyzed. Because the phrase “very anxious” is the dominant emotion of the sentence, and modifier “very” increases the intensity “anxious.” The output result displays that this sentence expresses negative sentiment, suggesting “my” emotions should be compensated. Five pieces of music and users are present to e-learner. It is shown in Figure 9.

In this paper, a 90-e-learner survey is used to check e-learner’s satisfaction of emotion compensation with a list of music and users under negative emotional situation. The evaluation results of e-learners are presented in Figure 10. The vast majority of e-learners are satisfied with the compensation list of music and users. We verify that the learner-oriented emotion compensation works well enough to alleviate e-learner’s negative emotions in e-learning.
Conclusions

This paper shows a study of learner-oriented negative emotion compensation in e-learning. Inspired from existing emotion regulation model in psycho, we design the architecture of learner-oriented negative emotion compensation. Further analysis of the learners’ behaviors in modes of delivery, we emphasize the emotion recognition of interactive text and the behaviors in CoD from the log of the Internet Education School of Xi’an Jiaotong University. In order to find e-learner’s personalized emotion regulative methods, three questionnaires (the Big Five, ERQ and NMR-S) are adopted. Integrating the results of surveys and existing technique, we propose the approach of e-learners’ negative emotion compensation based on recommender music and users. Furthermore, emotion as a subjective experience, a comprehensive measure is presented to evaluate the proposed approach. Both MAE and coverage are used to evaluate the performance of algorithm. On the other hand, a prototype system is created as a negative emotion compensation application to verify the usability of architecture of negative emotion compensation. A promising result is shown by a 90-e-learner survey, the proposed approach is practical and effective for alleviating e-learners’ negative emotion in e-learning.

From the analysis of e-learners’ behaviors in CoD, we found that both the content of the courseware and the limitations of service and network can cause the e-learner’s emotion change. It is suggestion that the construction and management of learning resource is as important as emotion interaction in e-learning.

Moreover, because emotion is complex, there is not universal taxonomy of emotion. Focusing on the goal and domain of research, researchers are to choose different lists of emotion (Kaminskas & Ricci, 2012). The study refers only to the negative emotions of anxiety, sadness, hopelessness, anger, shame and disgust in the learning domain. This is only because above six negative emotions take place most often in e-learning. However, negative emotions are not limited to these in learning and other domains. Doubtless, the proposed architecture and algorithm can be implemented to regulate e-learners’ negative emotions.

It is worthwhile to mention that the recommendation is not the only technique for negative emotion compensation. With the development of technology, we will find the suitable technique to absorb in negative emotion compensation. It is a great challenge to simulate realism of negative emotion compensation in e-learning.

Acknowledgements

The research was supported in part by the National Science Foundation of China under Grant Nos. 91118005, 91218301, 41261087, 61308120, National High Technology Research and Development Program 863 of China under Grant No. 2012AA011003, Key Projects in the National Science & Technology Pillar Program under Grant No. 2013BAK09B01, Cheung Kong Scholar’s Program. We would like to thank the anonymous reviewer for insightful comments.

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