MANAGING EMOTIONS IN SMART USER MODELS FOR RECOMMENDER SYSTEMS

Gustavo González, Beatriz López, Josep Lluís de la Rosa
Institut d'Informàtica i Aplicacions, Universitat de Girona, Campus Montilivi - Building P4, E-17071, Girona, Spain.
e-mail: gustavog@eia.udg.es; blopez@eia.udg.es; peplluis@eia.udg.es

Keywords: Emotions, recommender systems, smart user models, user modelling.

Abstract: Our research focuses on the development of methodologies that take into account the human factor in user models. There is an obvious link between personality traits and user preferences - both being indications of default tendencies in behavior, that can be automated by systems that recommend items to a user. In this work, we define an emotional component for Smart User Models and provide a methodology to build and manage it. The methodology contemplates the acquisition of the emotional component, the use of emotions in a recommendation process and the updating of the Smart User Model according to the recommendation feedback. The methodology is illustrated with a case study.

1 INTRODUCTION

Emotional Intelligence has been described as an important part of human decision-making (Goleman, 1995). It has been proved that, at a neurological level, emotions play a definitive role in the cognitive process (Joseph, 2001). Emotions should be taken into account when building a user model since there is an obvious link between personality traits and user preferences - both being indications of default tendencies in behaviour.

There are several approaches to computational models of emotions. Each one focuses its research according to its application in particular domains; some of them are described in (El-Nasr, et al., 1999). *Event appraisal models* proposed by (Roseman, et al., 1990) identify events with emotions. The OCC model (Ortony, et al.; 1988) provides a taxonomy, which labels general emotions based on a valence for the reaction to events and objects. Another example is the "Six Basic Emotions" model proposed by (Ekman, 1982) which is based on research into universal facial expressions. Other models are based on physiological simulation of emotions, where each emotion is defined in terms of the physiological reaction to it (Picard 1997).

(Kopecek, 2001) has defined a user model based on the personality and emotions, describing it as dialogue automata with properties of information systems. This work is supported by another study by (Green, et al., 2001) on neuronal biophysics and computation that tackles the matter of how to obtain the description of the behaviour of a system and how it can be modified by generating a series of interactions between the inputs and outputs, while the internal state of system is changing.

Our research concerns emotion modeling for recommender systems. Most recommender systems assist the user in a selection process based on interest and preferences of a single person or group of people (Sanguesa, et al., 2000). For doing so, recommender systems maintains a user model in which objective features of the products the user has been interested in the past as well as subjective features regarding the evaluation of such process are stored. Then, together with objective and subjective characteristics, we try to represent the emotional state of the user in what we call *Smart User Models*.

Providing user models with an emotional component, traditional recommender systems can improve the interaction with the user. Then, if user requirements regarding a product or service are satisfied, he/she will probably use the system again. Moreover, if the answer is complemented with the experience of having an affective deal with the lender of the service, the satisfaction degree and confidence perceived by the user is greater, and so probabilities of further use of the system (González, et al., 2002).

In this paper, we introduce our methodology to build and manage the emotional part of the Smart User Model. This paper is organised as follows. In section 2, we provide several definitions regarding the different representational levels for the Smart User Model (*SUM*). Then, we describe in section 3 the methodology proposed to deal with the emotional component of the *SUM*. We continue on section 4 with a case study, and we end in section 5 with some conclusions and discussion.

2 DEFINING EMOTIONAL FEATURES IN SMART USER MODELS

A *Smart User Model* (*SUM*) is an adaptive user model, which captures the evolution of the user regarding his/her emotions (González, 2003). The *SUM* should be then an artificial representation of the user. For achieving it, we distinguish two representational levels: the computational and the domain level. Following notation is given to represent formally the mental features of a user at the different levels.

2.1 Computational Level

Let be ***L*** the ***set*** of ***attributes,*** which represent the *features*, and *behaviours* of a user at the computational level composed by three dimensions:

$$A^O = \{a_1^O, a_2^O, a_3^O, ..., a_i^O, ..., a_n^O\}$$

$$A^S = \{a_1^S, a_2^S, a_3^S, ..., a_j^S, ..., a_m^S\}$$

$$A^E = \{a_1^E, a_2^E, a_3^E, ..., a_k^E, ..., a_\ell^E\}$$

$\boldsymbol{A^O}$ is the finite set of objective attributes of user. These can be provided by the user or acquired from any database. Relate the name, age and socio-demographic information of the user. $\boldsymbol{A^S}$ is the finite set of subjective attributes of user. These are the personal judgment that the user performs according to her/his impressions, feelings and opinions or an arbitrary expression of his/her private preferences. These features can only be acquired through user interaction with external environment and the system. Finally, $\boldsymbol{A^E}$ relates psychological traits and personality, such as joy, surprise, sadness, anger, disgust, etc.

Each attribute can take values in a given domain, using the following notation: $v_i^O = value(a_i^O)$, $v_j^S = value(a_j^S)$, $v_k^E = value(a_k^E)$

With those set of attributes, it is possible to define a Smart User Model as follow:

Definition 1: A *Smart User Model*, *SUM,* is the collection of attributes-value pairs that characterize the user.

$$SUM = \left\langle \begin{array}{l} \left[(a_1^O, v_1^O), (a_2^O, v_2^O), ..., (a_i^O, v_i^O), ..., (a_n^O, v_n^O)\right], \\ \left[(a_1^S, v_1^S), (a_2^S, v_2^S), ..., (a_j^S, v_j^S), ..., (a_m^S, v_m^S)\right], \\ \left[(a_1^E, v_1^E), (a_2^E, v_2^E), ..., (a_k^E, v_k^E), ..., (a_\ell^E, v_\ell^E)\right] \end{array} \right\rangle$$

In above definition it can distinguish, the objective component of the *SUM*, U^O, the subjective component U^S and the emotional component, U^E, as follows:

$$U^O = \left[(a_1^O, v_1^O), (a_2^O, v_2^O), ..., (a_i^O, v_i^O), ..., (a_n^O, v_n^O)\right]$$

$$U^S = \left[(a_1^S, v_1^S), (a_2^S, v_2^S), ..., (a_j^S, v_j^S), ..., (a_m^S, v_m^S)\right]$$

$$U^E = \left[(a_1^E, v_1^E), (a_2^E, v_2^E), ..., (a_k^E, v_k^E), ..., (a_\ell^E, v_\ell^E)\right]$$

Then, we get the following alternative definition:

$$SUM = \langle U^O, U^S, U^E \rangle$$

The emotional component represents then, the different moods that the user manifests. Since too many attributes make the emotional component of the *SUM* inoperable for a recommendation process, we resume the emotional component of the user in a single value, that we have called the emotional state. The emotional state allows to know general range for emotions indicating whether an emoting individual is feeling *pleasant* versus *unpleasant*, *dominating* versus *vulnerable*, and *activated* versus *quiescent*. Such states can be classified in:

-Markedly Negative: This state includes the affective states or moods typically of a user with bad humour. As consequence, the suggestions of the recommender systems have to be carefully studied.

-More Negative: This range of affective states is a degree more flexible than the first one. In the same way includes moods with “high sensibility”, that should be taken into account at the moment of the recommendations.

-Neutral: Users in these affective states are doubtful. They don’t crack under pressure but they may still become anxious, depressed or very nervous when things become difficult. The users are more propensities to receive a wide range of recommendations than in the previous cases.

-More Positive: In this range of moods the user has a relative self-control. He/she is open to new, non-expected recommendations.

-Markedly Positive: At this state, any kind of excitation from the environment, including unexpected recommendations, are usually welcomed.

Such emotional information is useful for the recommendation process, for which we have developed a mechanism based on attribute *activation* and *inhibition*. Note that the emotional state is computed as required (see section 3.2 for the procedure) but it is not explicitly stored at *SUM*.

2.2 Domain Level

The domain level is the particular environment in the real world in which the user is modelled. It is marked by specific characteristics and organization according to design goals of the software applications.

Let be ***D*** a set of attributes that define a given domain.Let be $A^D \subset D$ the ***set*** of characteristics, properties and organization or operation of an item (object or service) in a given domain *D*.

$$A^D = \{a_1^D, a_2^D, \ldots, a_h^D, \ldots, a_p^D\}$$

Let be $A^I \subset D$ a ***set*** of interests of a user in particular objects or services in a domain *D*.

$$A^I = \{a_1^I, a_2^I, \ldots, a_i^I, \ldots, a_p^I\}$$

Let be A^U the socio-demographic features of the user in the domain *D*, normally introduced in a “login” procedure.

$$A^U = \{a_1^U, a_2^U, \ldots, a_k^U, \ldots, a_r^U\}$$

Among all the attributes at the domain level, we distinguish the attributes that represent emotional connections between the attributes and the emotional state. They are called *excitatory attributes*, $E^D, E^D \subseteq \{A^D \cup A^I\}$. In each domain, an *activation table* that relates emotional states with excitatory attributes is defined (see Table 1).

Excitatory attributes	Markedly Negative	More Negative	Neutral	More Positive	Markedly Positive
Price	-0.8	-0.3	-0.2	0.2	0.4
Capacity	-0.7	-0.2	-0.1	0.1	0.2
Curiosity	0.4	0.5	0.6	0.7	0.8
Food quality	0.3	0.4	0.5	0.6	0.9
Quality/Price relation	-0.6	-0.5	-0.4	0.1	0.3
Efficient service	-0.8	-0.6	-0.5	0.2	0.3

Table 1. A possible activation table.

Each excitatory attribute, e^D, has an *activation degree*, $AD_i(e^D) \in$ [-1, 1] for a given emotional state *i*. A low value close to -1, means *inhibition*, that is, the recommender system can ignore it in the recommendation process. A high value close to 1, means *activation*, that is, the recommender systems should be take especially care of the attribute when doing the recommendation.

This paper focuses on the definition and management of emotional features. For details about the objective and subjective features, see (González, 2003).

3 EMOTIONAL FEATURES MANAGEMENT

To deal with emotional features of the user we have defined a methodology based on three stages: *initialisation*, *update* and *advice*.

The *initialisation stage* consists in the acquisition of emotional features of the user to compound the Smart User Model. The *advice stage* proposes a method to help recommender systems to provide suggestions according to the emotional state of the user. The *update stage* consists in the keep informed the Smart User Model due to the emotional changes of the user according to the most recent interactions. So the values of the activation table are updated.

3.1 Initialisation

The initialisation of emotional features about the user can be acquired by means of the *Emotional Intelligence Test* (EIT) that has a 98% degree of confidence (Jarabek; 2001). The EIT provide information about the user which is appropriately assigned in the different emotional features of the user at *SUM*. Thus, the initialisation stage is conformed by two steps: 1) The emotional intelligence test and 2) Information distribution.

3.1.1 The emotional intelligence test

The EIT provides a set of parameters from the user, which can be classified and labelled. Such parameters are five: *Self-conscience; Self-Control; Goal-Orientation and Motivation; Self-Expression and Social-ability; and Empathy.* Each parameter is defined in [0, 1] (see Figure 1).

3.1.2 Information distribution

The parameters provide information about the user from which we wish to compute the current emotional attributes of the user, a_i^E, of the *SUM*. In our model, we define as many emotional attributes as moods provided by the psychology studies of (Scherer, 1988). Moods are affective states as anger, angry, and hopeless. Each parameter of the *EIT* has a set of mood related. To know the corresponding value of each mood (emotional attribute) of the user from the *EIT* parameters we perform the distribution according to the relationship between mood and parameters shown in table 2.

Let be Par the set of parameters, namely:

Par = {Self-conscience, Self-Control, Goal-Orientation, Self-Expression, Empathy}.

Each parameter $\boldsymbol{p_i} \in$ Par has a value, VAL($\boldsymbol{p_i}$).

Let be *Mood* the set of the all-possible user moods, Mood = $\{m_1, m_2, m_3, ..., m_k, ..., m_n\}$. A set of moods is defined for each parameter, $\forall$ parameter $\boldsymbol{p_i} \in$ Par, $\exists$ a set of moods $Mod(p_i) \subset Mood$. At this step a value of mood m_{ij}, VAL(m_{ij}), is computed for each mood of each parameter, that is:

$$\forall \boldsymbol{p_i} \in \text{Par}\, ;\ \forall\ m_{ij} \in Mod(p_i)$$

$$\text{VAL}\,(m_{ij}) \leftarrow \text{VAL}(\boldsymbol{p_i})$$

Parameter \ Valence	(- -) [0, 0.2)	(-) (0.2, 0.4]	(- +) (0.4, 0.6]	(+) (0.6, 0.8]	(+ +) (0.8, 1]
Self-conscience	selfish	Afraid Anguished Frightened Helpless Scared	Confident Courageous Cowardly	Lively Stimulated	happy
Self-control	Aggressive Desperate fed up Intolerant vengeful	Annoyed Discontented Disgruntled Disgusted Exasperated Furious Hopeless Impatient Tense Worried	Agitated Amazed Anxious Astonished Calm Curious Excited Nervous relaxed	Eager Jubilant Passionate Serene	Ecstatic Elated
Goal-orientation and motivation	Apathetic Dejected listless	Bored Confused Despondent Disappointed Discouraged Disdainful Dismayed Gloomy grief-stricken Hesitant Tired	Carefree Doubtful Resigned Stubborn	Hopeful Interested Satisfied	Contented
Self-expression and social-ability	Angry Depressed Sad unhappy	Ashamed Embarrassed Nostalgic	Indifferent Shy Surprised regret	at ease Fascinated Grateful Inspired Joyful sensual	Affectionate Cheerful
Empathy	Lonely Offended Outraged repelled	Distrustful Embittered Jealous Hostile	Compassionate Earnest Proud	Enthusiastic Humble Respectful Tender Warm-hearted	Amused Delighted

Table 2. A possible table of relations between parameters and valences through the moods

Be aware that VAL ($\boldsymbol{p_i}$)$\in$ [0, 1], so VAL(m_{ij})$\in$ [0, 1] too.

At the end of this step, each mood $m_{ij} \in$ *Mood* has a value. Since we define an emotional attribute, a_i^E for each mood, we get that $A^E = Moods$, and so we obtain the emotional component U^E of the *SUM*.

3.2 Advice

The goal of this stage is to take advantages of the information of the emotional state of the user, U^E of the *SUM*, in the domain level.

The advice step consists on providing emotional information to recommender systems in order to allow the improvement of the recommendations made to the user. For each domain a set of attributes, E^D, will be activated or inhibited depending on the emotional user state, and accordingly to the activation table. In order to obtain the emotional state of the user from the emotional features, we propose a two-step methodology: *Valence aggregation* and *labelling.*

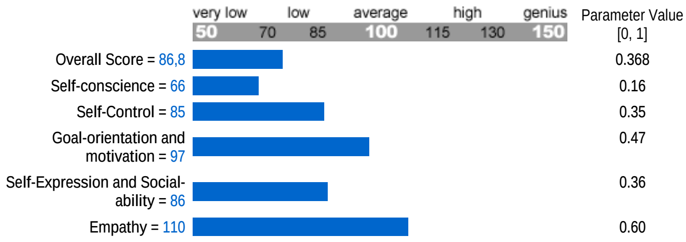

Figure 1. A sample of the results of the Emotional Intelligence Test

3.2.1 Valence Aggregation

A valence is the degree of attraction or aversion that a person feels toward a specific object or event. Possible values of valences range from (+ +) to (- -).

According to the psychology studies, each mood (our emotional features) can be labelled with a valence. For example, eager is +, angry is -. Table 2 shows the complete relationship between moods (on the cells) and valences (columns). Then, from the emotional component of the user, we can: 1) Compute the individual value of each valence; 2) Compute the global value for all valences. The result of the second step provides us with a global mood of the user.

Sub-step 1: Valence computation

At this step, we spread the information of moods to each valence. For each valence, ***valence$_i$***, a set of moods, $Mod(valence_j)$ is defined,

$\forall$ valence ***valence$_i$*** $\in$ *Valence*, $\exists$ a set of moods $Mod(valence_i) \subset Mood$. Then, we compute the value of the valence, VAL($valence_j$) for each *valence* $\in$ *Valence* as follow:

$$\forall\, valence_j$$
$$\forall\, m_{ij} \in Mod(valence_j)$$

$$\mathrm{VAL}\,(valence_j) = \frac{\sum_{j=1}^{j=n} VAL(m_{ij})}{Nm} \qquad \textbf{(1)}$$

Where Nm = Cardinality of $Mod(valence_j)$, and VAL $(valence_j) \in [0,1]$

Sub-step 2 : Global mood of the user

At this step, we compute the final value of all the valences for the user, *GlobalMood*, as

$$GlobalMood = \frac{\sum_{j=1}^{j=Numval} VAL(valence_j)}{Numval} \qquad \textbf{(2)}$$

Where *Numval* = Number of valences. The result *GlobalMood* is defined in [0, 1].

3.2.2 Labelling

At this step, the global mod value is fuzzyfied in order to know the emotional state of the user according to the labels shown in the table 3, which correspond to categories according to the relatively temporary state of feelings in the user.

Label	Markedly Negative	More Negative	Neutral	More Positive	Markedly Positive
x_i	[0, 0.2)	(0.2, 0.4)	(0.4, 0.6)	(0.6, 0.8)	(0.8, 1]

Table 3. Labels for the emotional state.

Several membership functions are possible to define the fuzzy sets. As a start point of our research and taking into account the computational efficiency and the posterior discretization of the results we have chosen trapezoidal *membership functions (MFs).* Figure 2 shows the fuzzy values proposed.

After fuzzyfiying the *globalmood* value of the previous step, we get the corresponding emotional state of the user. Such emotional state is used to access the activation table and know the activation degree of the emotional attributes. Such emotional information will be taken into account in a recommendation process.

3.3 Update

At this stage, the activation degree of excitatory attributes, E^D at the domain level are updated according to the feedback of the recommender system.

A feedback value is provided for each recommendation, this value is between the [-1,1] interval. Then, when the excitatory attribute has a high activation degree, this is updated according to the following expression:

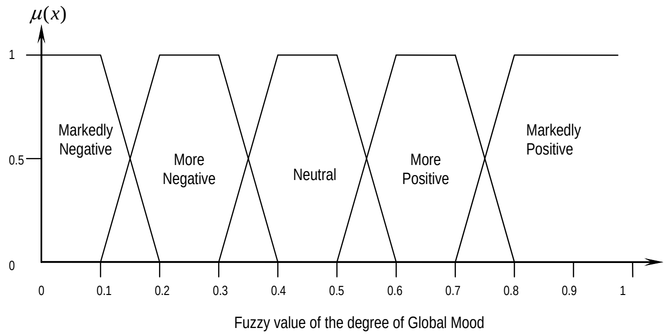

Figure 2. Membership functions for the Global Mood

$$AD_i(e^D) = \varphi AD_i(e^D) + (1-\varphi)\,Feedback \quad ;$$

when $AD_i(e^D) \geq 0$ **(3)**

Otherwise,

$$AD_i(e^D) = \varphi AD_i(e^D) - (1-\varphi)\,Feedback \quad ;$$

when $AD_i(e^D) < 0$ **(4)**

Where φ is the factor of system evolution dynamics to *reward* or to *punish* the correspondent excitatory attribute according to the feedback from the recommendation process (Jonker and Treur, 1999).

The activation equation 3 and 4, guarantee that:

1. Attributes with a high activation degree, with a positive feedback, will diminish its distance to the maximum activation degree (value of 1).
2. Attributes with a high activation degree, with a negative feedback, will become less important in a recommendation process for the emotional state *i.*
3. Attributes with a low activation degree, with a positive feedback, will diminish its activation degree in the recommendation process for the emotional state *i.*
4. Attributes with a low activation degree, with a negative feedback, will increase the distance to the minimum value activation degree (value -1).

4 CASE STUDY

In this section, we illustrate with an example the methodology proposed. We get the emotional component of the *SUM* of the user Juan Valdez®, and then use it to recommend to the user a restaurant by means of a recommender system. Afterwards, the feedback of the recommendation is used to update the activation table.

4.1 Initialisation

Here we illustrate how the emotional component of Juan Valdez® is acquired.

4.1.1 Emotional Intelligence Test

Let's suppose that the Emotional Intelligence Test of Juan Valdez® results are the ones shown in the Figure 1: (Self-conscience = 0.16, Self-control = 0.35, Goal orientation and motivation = 0.47, Self-expression and social-ability = 0.36, Empathy = 0.60).

4.1.2 Information Distribution

First of all, we distribute the ***self-conscience*** value to all the corresponding moods. That is,

Mod(self-conscience) = {weak, afraid, anguished, frightened, helpless, scared, confident, courageous, cowardly, lively, stimulated, happy}.

So, value(weak) = value (afraid) = value (anguished) = value (frightened) = value (helpless) = value (scared) = value (confident) = value (courageous) = value (cowardly) = value (lively) = value (stimulated) = value (happy) = 0.16

Analogously, we distribute the rest of the parameters.

4.2 Advice

Here we illustrate how the emotional component of the user can be applied in a recommender system.

4.2.1 Valence Aggregation

This step is compound by two sub-steps: Valence computation and Global Mood of the user.

Sub-step 1: Valence Computation

Let's start with the computation of the (--) valence. The moods corresponding to this valence, *mood(--)*, are the following (see table 2):

Mod(--) = {weak, aggressive, desperate, fed up, intolerant, vengeful, apathetic, dejected, listless, angry, depressed, sad, unhappy, lonely, offended, outraged, repelled}

Then, the individual computation of the (--) valence is performed according to equation (1) as follows:

VAL(--) = [VAL(weak) + VAL(aggressive) + …+ VAL(repelled)] /*Nm*

VAL(--) = [0.16 + 0.35 + 0.35 + 0.35 + 0.35 + 0.35 + 0.47 + 0.47 + 0.47 + 0.36 + 0.36 + 0.36 + 0.36 + 0.60 + 0.60 + 0.60 + 0.60] /17

VAL(- -) = 0.4211

Analogously we can compute the value of the rest of the valences:

VAL(-) = 0.3924

VAL(- +) = 0.3804

VAL(+) = 0.4119

VAL(+ +) = 0.4062

Sub-step 2: Global Mood of the user

Finally, we compute the global mood of the user according to equation (2).

GlobalMood = VAL(--) + VAL(-) + VAL(-+) + VAL(+) + VAL(++)/Numval

GlobalMood = [0.4211 + 0.3924 + 0.3804 + 0.4119 + 0.4062]/5

GlobalMood = 0.4024

4.2.2 Labelling

The global mood of Juan Valdez® has been a positive value = 0.4024. This value corresponds to the ***Neutral*** label as show the Figure 2.

4.2.3 Advice mechanism

Let's suppose that the excitatory attributes in the restaurant domain are: price, capacity, curiosity, food quality, quality/price relation, efficient service.

$E^D =$ {price, capacity, curiosity, food quality, quality/price relation, efficient service}

Remember that our mechanism consists in to give activation degree between [-1, 1] to all excitatory attributes. Table 1 summarizes the activations and inhibitions for the restaurant domain. Accordingly, we activate or inhibit the excitatory attributes in relation with the emotional state of the user performed. Since Juan Valdez® has a neutral emotional state, the following activations and inhibitions hold:

- Activate: curiosity (0.6), food quality (0.5)
- Inhibit: price (-0.2), capacity (-0.1), quality/price relation (-0.4) and efficient service (-0.5).

With these activations and inhibitions, the Juan Valdez® Smart User Model advises the recommender system in order to decide more suitable items in the restaurant domain according to the current emotional state of Juan Valdez®.

4.3 Update

In our example, the recommender system has suggested to Juan Valdez® a restaurant getting the following feedback from the recommender system: 0.9. We know the global mood of Juan Valdez®, which is Neutral. From table 1, we know the activation degree for each of excitatory attribute, which has contributed to the recommendation.

If we take the first excitatory attribute, curiosity, which has been activated in the recommendation process, and taking into account that the feedback has been positive, we update the activation degree of the curiosity attribute according to equation 3 (with φ = 0.5):

$$AD_i(curiosity) = 0.5*0.6 + (1 – 0.5)*0.9 = 0.75$$

Analogously, we get the new values for food-quality: 0.70. Regarding price, it has been inhibited in the recommendation process, so equation 4 applies:

$$AD_i(price) = 0.5*(-0.2) – (1 – 0.5)*0.9 = -0.55$$

Analogously, we get the values for capacity (-0.5), quality_price_rel(-0.65), and efficient_service (-0.70).

5 CONCLUSIONS

In this paper, we have introduced a new approach to model the emotional state of the user in what we define a Smart User Model. The model is based on attribute-value pairs, in which attributes corresponding to the emotional component are computed on the basis of psychological works. This methodology can be used to both, acquire user personality traits and deliver the user emotional features to recommender systems. The methodology is based on three steps: initialisation, advice and update. First, initialisation is based on Emotional Intelligence. Second, the use of the emotional component of the model in a recommendation process is achieved through the activation and inhibition of domain features in a given application. Finally, the feedback of the recommendation allows the updating of the connections between applications that use the Smart User Model and the emotional state of the user. In addition, we have illustrated the methodology with case study.

Our next step goes towards integrate our Smart User Model with the context in where recommendations are performed (Van de Velde, 1997), (Bianchi-Berthouze and Lisetti, 2002). The knowledge of the current situation of a user, combined with the knowledge of his/her Smart User Model can provide remarkable results in the field of recommenders systems.

6 ACKNOWLEDGMENT

This research has been supported through the Spanish project MCYT DPI2001-2094-C03-01.

REFERENCES

Bianchi-Berthouze, N., Lisetti, C.L. 2002, 'Modeling Multimodal Expression of User's Affective Subjective Experience'. *User Modeling and User-Adapted Interaction*, vol. 12, No. 1, pp. 49-84.

Ekman, P. 1982, *Emotion in the human face*. 2nd Edition. Cambridge University Press, Cambridge, UK.

El-Nasr, M.S., Ioerger, T. R. and Yen, J. 1999, 'PETEEI: A PET with Evolving Emotional Intelligence', *In Proceedings of Autonomous Agents Conference '99, WA*.

Goleman, Daniel. 1997, *Emotional Intelligence: Why it can matter more that IQ*. Bantam Books, New York.

González, G., López, B. & de la Rosa J. Ll. 2002. 'The Emotional Factor: An Innovative Approach to User Modelling for Recommender Systems', *In Proceedings of AH2002 Workshop on Recommendation and Personalization in e-Commerce*, Málaga, Spain, pp. 90-99.

González, G. 2003. Towards Smart User Models for Open Environments. M.Sc. Thesis. *Institut d'Informàtica i Aplicacions*. Universitat de Girona. Girona, Spain.

Green, S., Hurst, L., Nangle B., Cunningham, P., Somers, F., Evans, R. 1997, 'Software Agents: A review', *Technical Report TCS-CS-1997-06 Departament of Ciompuer Science*. Trinity College, Dublin.

Jarabek, I. (2001). *Emotional Intelligence Test, 2nd Revision*, Plomeus Inc. QueenDom.com™ [On-line] Available at: http://www.queendom.com/tests/iq/emotional_iq_r2_access.html

Jonker, C. M. and Treur, J. 1999, 'Formal analysis of models for the dynamics of trust based on experiences', *In Proceedings of MAAMAW'99. Lecture Notes in AI*, vol 1647, Springer Verlag, pp 221–232.

Joseph, S. 2001, 'AI', *J@pan Inc.*, [On-line] Available at: http://www.japaninc.net/article.php?articleID=514 [Accessed January 15th 2002].

Kopecek, I. 2001, 'Personality and Emotions - Finite State Modelling by Dialogue Automata', *In Proceedings of UM 2001 Workshop on Attitudes*, University of Bari, pp. 1-6.

Ortony, A., Clore, G., Collins, A. 1988, *The Cognitive Structure of Emotions*. Cambridge, Cambridge University Press.

Picard, R. W. 1997, *Affective Computing*. M.I.T. Press, Cambridge

Roseman, I.J., Martin S. S. & Paul E.J. 1990, 'Appraisals of Emotion-Eliciting Events: Testing a Theory of Discrete Emotions' *Journal of Personality and Social Psychology*, The American Psychological Association, Inc. , vol. 59, No. 5, pp. 899-915.

Sanguesa, R., Cortés U., Faltings B. 2000, Workshop on Recommender Systems, Autonomous Agents 2000, Barcelona, Spain.

Scherer, K. R., (Ed) 1988, Apendix F. 'Labels describing affective states in five major languages', *Facets of emotion: Recent research*, Hillsdale, NJ: Erlbaum, pp. 241-243, [On-line version revised by the members of the Geneva Emotion Research Group], Available at: http://www.unige.ch/fapse/emotion/resmaterial/resmaterial.html [Accessed May 6th 2003],

Van de Velde, W. 1997, 'Co-habited Mixed Realities', *In Proceedings of IJCAI'97. Workshop on Social Interaction and Communityware*, Nagoya, Japan.