Embedding Emotional Context in Recommender Systems

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Abstract

Emotional context is becoming a promising paradigm to develop more intuitive and sensitive recommender systems. Ambient Recommender Systems, arise from the analysis of new trends on the exploitation of the emotional context in the next generation of recommender systems. We explain some results of these new trends in real-world applications through the Smart Prediction Assistant (SPA) platform implemented in an Intelligent Learning Guide. While most approaches to recommending focus on algorithm performance, SPA makes recommendations to users on the basis of emotional information acquired in an incremental way. This article provides a cross-disciplinary perspective to achieve this goal in such recommender systems through the SPA platform. The methodology applied in SPA is the result of a bunch of technology transfer projects for large real-world recommender systems.

Introduction

Over the last decade, research on recommender systems has focused on performance of algorithms for recommendations; and improved ways of building user models to map user preferences, interests and behaviors into suggesting suitable products or services (Burke 2001). At the same time, several recommendation approaches and techniques have been developed in a variety of domain-specific applications (Adomavicius and Tuzhilin 2005).

Whereas many techniques have been proposed in user modeling, little attention has been paid on analyzing the emotional information involved in this modeling process.

In the real world, user's objective requirements can be forgotten and forsaken when his/her emotional needs are satisfied. The users always transmit their decisions together with emotions. For this reason, most consumer-centered companies are interested in detecting existing links between users' actions and the emotions to automatically personalize and analyze user retention rates, loyalty rates, churn rates, cross-selling among other variables. Moreover, variables such as surprise, joy, disgust, empathy, feeling and, in general, users' emotional responses towards company products and services cannot be explicitly detected with current approaches. So, the questions that we try to answer in this article are: How to improve Recommender Systems and make them more pleasant to the user through the automatic perception of his/her emotional context? How can we build a more effective and satisfactory interaction in recommender systems? Can we automatically manage user's emotional awareness in recommender systems?

In order to answer these questions first, user models should be built with learning capabilities from user's emotional awareness in recommender systems. Therefore, traditional approaches require enriched support in future emerging information society technologies such as Ambient Intelligence and Pervasive Computing. In this kind of future emerging technologies the development of Smart Adaptive Systems (González, López and de la Rosa 2005) is a cornerstone for personalizing services in the next generation of open, distributed, decentralized and ubiquitous recommender systems. Secondly, such recommender systems should learn from the user's interactions everywhere and anytime in nonintrusive way. Indeed, the complexity of modeling a user in real contexts is not a simple task, given that the context is a multidimensional parameter involving time, location and subjectivity in perceptions and emotions (Minsky 2006).

With the vision of Ambient Intelligence (AmI) humans are the centre of new applications. AmI will be able to discover, among others, emotional needs when users interact with ubiquitous recommender systems in everyday life (Remagnino and Foresti 2005). An Ambient Recommender System proactively operates as a ubiquitous intelligent adviser on behalf of users in an everyday context; it is sensitive, adaptive and responsive to their needs, habits and emotions in real time while they reduce their information overload.

The article is structured as follows: In Section 2, we describe related work and new trends on the exploitation of the emotional context with a cross-disciplinary perspective to build user models in Ambient Recommender Systems. In section 3, we explain the methodology to manage emotions in recommender systems. Next, we describe SPA (Smart Prediction Assistant) a customer intelligence platform that embeds the user's emotional intelligence in recommender systems. In Section 5, we test our approach in a large e-commerce Intelligent Learning Guide recommender system and we analyze successful results. In

Section 6, we facilitate a discussion about lessons learned with our deployment. Finally, we provide some conclusions and set targets for future work.

Emotional Context in Recommender Systems

It is well known that emotions play an essential role in user's decision making (Picard et al. 2006). In particular, the emotional factor influences the rational thinking when a user receives any recommendation. The emotional factor is defined as the relevance that each user gives to differential values of items (i.e., events, services, products), which are demonstrated in the user's decision-making process by means of his or her actions.

Fig. 1. Towards the next generation of Ambient Recommender Systems: an extended approach from R. Burke

We expand and tackle some challenges of the approach of Burke (Burke 2001) surrounding knowledge sources and user profiles by users' context, in particular, the user's emotional context. As we show in the Fig. 1, this kind of Ambient Recommender Systems should represent in a holistic way several relevant properties (e.g., cognitive context, tasks context, social context, emotional context, cultural context, physical context and location context among others variables) according to the user's circumstances, using existing and new techniques for recommendations. For instance, the daily life of nomadic users of recommender systems in the home environment, workplace, car, leisure time and tourism, among other scenarios, can be simplified and enriched by satisfying their interests, preferences and understanding their emotional context.

To achieve these objectives we have developed a synergistic approach combining a model of the user's emotional information with machine learning and intelligent agents in the so-called *Smart User Models* (*SUMs*) (González, López and de la Rosa 2005). They act like unobtrusive intelligent user interfaces to acquire, maintain and update the user's emotional information through an incremental learning process in everyday life.

In particular, *SUM*s can provide to Ambient Recommender Systems the capability to manage the user's emotional context, acquiring his or her emotional intelligence. This capability is becoming increasingly important for modeling humans holistically. Consequently, the following properties have been taken into account in our methodology to achieve tailored personalization:

- Smartness provided by users' affective factors and context-awareness by integrating emotional capabilities.
- Human-centered interaction improved by agents that act on behalf of users in flexible ways (i.e. in pro-active, reactive and social ways). Through a multi-agent architecture *SUM* is also able to resolve the pro-active and autonomous pre-processing of raw data acquired from user's multiple interactions in several application domains and in a multi-modal way.
- Continuous modeling through machine learning techniques in open environments. *SUM* learns in an incremental way from users' continuous interactions in complex situations in which the emotional context is relevant to suggestions made by the recommender systems.

Some other approaches in recommender systems consider contextual information associated with the ambient intelligence scenarios. For instance, relevant research work is being carried out on users' emotional factors in recommender systems (Masthoff 2005) to better understand users in complex situations. At the same time, challenging research initiatives for defining standards in emotion-oriented computing are becoming increasingly relevant (W3C 2006).

Currently, there are few commercial recommender systems which consider these sensibilities for creating user models. Most systems use statistical techniques. Some others use data mining techniques mixed with relational marketing concepts to create behavior patterns of users and consumers and then classify them according to rules. However, none of these recommender systems consider the emotional context as fundamental component of analysis to create truly personalized and individualized user models according to preferences and interests. Most importantly, they do not have capabilities for smart behavior, that is, they should be able to learn in an incremental way and produce effective recommendations in a wide variety of complex circumstances.

Automatic Learning of Emotional Context through User's Emotional Intelligence

According to Salovey and his colleagues emotional intelligence is "*a type of social intelligence that involves the ability to monitor one's own and others' emotions, to discriminate among them, and to use the information to guide one's thinking and actions*" (Mayer et al. 2003). Emotional Intelligence can be measured, ranging from feelings of boredom to feelings of happiness and euphoria, from hostility to fondness.

We have taken advantages from Emotional Intelligence research for developing socially intelligent recommender systems as a critical step towards enabling them to be more intuitive with the user since there is an obvious link between personality traits and user preferences - both being indications of default tendencies in behavior. Our methodology provides a high added value to existing approaches in recommender systems through the users' emotional information, so we highlight the relevant stages to acquire, manage and update the emotional information about users:

1. Initialization stage: this stage consists of the acquisition of users' emotional features based on a gradual and noninvasive emotional intelligence test (i.e Gradual EIT). Particularly, in this work we apply the so-called the Four-Branch Model of Emotional Intelligence which can be measured through the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT V2.0) (Mayer et al. 2003). Particularly we emphasize that each emotional state can be labeled with a valence. In the context of emotional information a valence is the degree of attraction or aversion that a person feels toward a specific object or event

2. Advice stage: this stage consists of providing emotional information to recommender systems to improve recommendations made to the user. It is based on activation or inhibition of excitatory attributes from each domain of interaction according to the emotional information.

3. Update stage: this stage keeps the *SUM* informed of user changes according to recent interactions based on reward and punish mechanisms.

For the sake of extension, we encourage the reader to consult details on the formal definition of *SUM* and the methodologies developed in (González, López and de la Rosa 2005).

Smart Prediction Assistant: Embedding Emotions in Real-World Recommender Systems

Smart Prediction Assistant (SPA) is an innovative customer intelligence platform based on technology transfer results from several R&D projects in which results with high impact on the e-commerce domain have been obtained. The SPA customer intelligence platform is an advance in the evolution of Habitat-Pro™ V2.5, which was a supervised platform to batch-process user profiles. SPA is now a semi-supervised platform that automates several time-consuming manual processes in both off-line and on-line environments to build dynamic and emotional user models for recommender systems. SPA improves the existing platform, embedding powerful incremental learning mechanisms to create highly accurate emotional intelligence-based models. To achieve this objective SPA exploits heterogeneous, multi-dimensional and massive databases to extract, pre-process and deliver distilled user LifeLogs.

The user's LifeLog is a complex set of all the raw data about the user generated by the interaction with multiple applications in several domains in a multi-modal way (i.e. socio-demographic data, web usage data, transactional data, explicit ratings, attribute databases, physiological signals, etc). Thus, SPA can suggest in an automatic way individualized messages for each user. SPA is also able to create in real-time and in an automatic way individualized Human Values Scales for each user according to his/her dominant attributes.

The following components have been developed in SPA:

1. LifeLogs Pre-processor Agent: This agent replicates itself proactively for each user. Its function is to pre-process raw data in on-line and off-line environments.
2. Smart Component: This component implements advanced algorithms and methods for incremental learning in order to accurately predict user behavior. It has graphics tools to monitor and manage scorings, classifications, rankings of attributes, items and users, user propensity and others capabilities.
3. Attributes Manager Agent: This agent is able to create, extract, select, and fuse attributes in order to evaluate similar attributes for multiple domains of interaction and also to contrast them in an automatic way. This agent automatically detects the level of sensibility of each user for each of his/her dominant attributes by automatically assigning weights (relevancies).
4. Messaging Agent: This agent is able to automatically generate emotional arguments from users' dominant attributes by using messages in each application domain for each product. This agent acts on behalf of marketing retailers to define individualized communication styles for each user.
5. Intelligent User Interface: It is an add-on component to manage an individualized and personalized Human Values Scale of each user in his/her life cycles. It embeds an intelligent feedback mechanism that enables:

a. The analysis of diverse values from the individualized scale of each user in real time.

b. The definition of the coherence function between a user's actions and his/her implicit and explicit preferences in a recommender system.

For reason of clarity, in this article we only describe our deployment using the first four components of SPA. For details about methodology implemented in the fifth component of SPA we encourage the reader to consult details in (Guzmán et al. 2005).

A Business Case: The Intelligent Learning Guide Recommender System

We have deployed SPA in a large e-Commerce Intelligent Learning Guide with more than three million users, namely emagister.com. Usually, in this kind of recommender

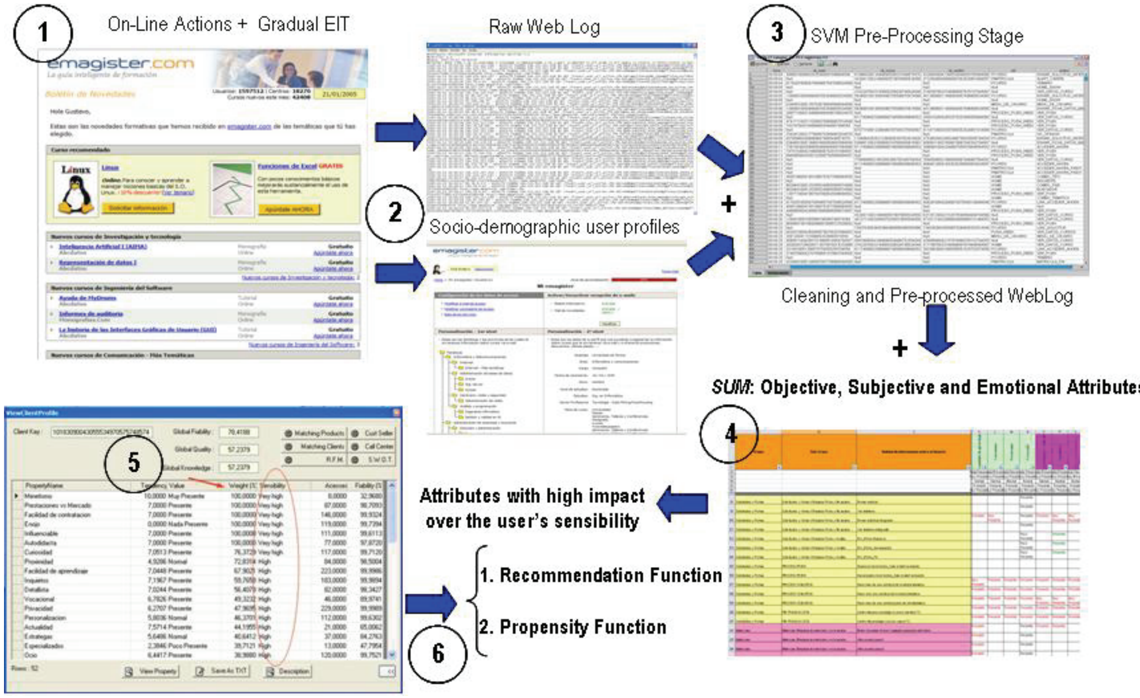


Fig. 2. Iterative automatic process to discover, manage and update emotional attributes in SPA

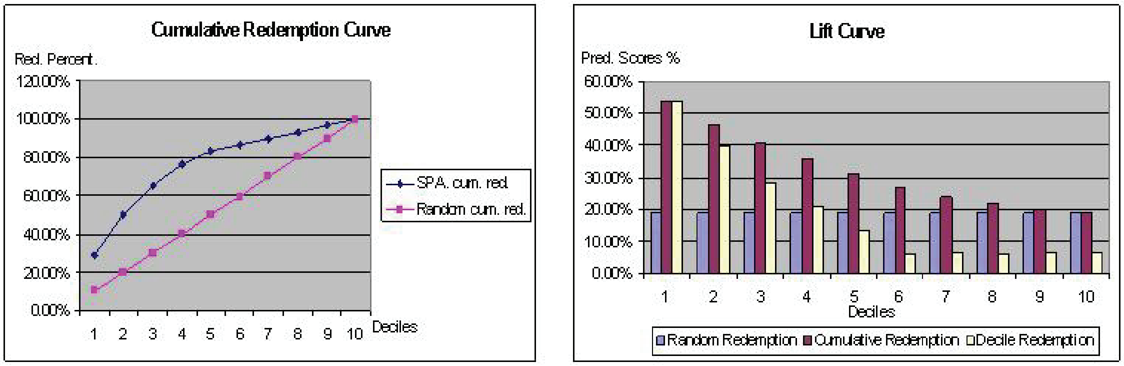
system, the suggestions are delivered through a combination of the user's explicit preferences and user feedback is acquired via click-stream analysis (i.e., implicit feedback) and/or user rating of the perceived quality of recommended items (i.e., explicit feedback), generating raw data to be analyzed. The user's decision making has been enriched and supported by measuring his or her sensibility to specific attributes in specific domains of training. In particular, not only are users advised in selecting the more relevant course to satisfy their preferences and interests, but they also intensify their satisfaction by discovering their sensibility to particular attributes that allow better communication via newsletters. In this scenario, SPA take advantage of the *SUM*s capturing both objective features of users and information related to their subjectivity in e-commerce applications.

Data Description

In this case, *SUM* gathers 75 objective, subjective and emotional attributes of 3,162,069 registered users till 14th March of 2006. The set of possible on-line user's actions on the web of emagister.com was 984. Data has been extracted from socio-demographic databases (i.e. user profiles with objective attributes) and WebLogs of user's implicit navigation habits (i.e subjective and emotional attributes discovered according to the users' answers given in the Gradual EIT). Specifically, we have ten suitable emotional attributes with different kind of valence for this business case: enthusiastic, motivated, empathic, hopeful, lively, stimulated, impatient, frightened, shy and apathetic. WebLogs are close to 50 Gb/month.

Process Description

First, a marketing strategy was designed whereby emotional attributes and their values are collected using the Gradual EIT implemented for each user through push and newsletters communications. When users answer questions (only one question every time that push or newsletters are received) related to their common day to day situations (opinions, tastes, pictures, etc), their impacted emotional attributes related with the questions are gradually activated (González, López and de la Rosa 2005). Finally, in order to maintain their emotional attributes and values updated each time that users open and surf the recommendation sent in Push or newsletters communications about training courses, the reward mechanism works to reinforce the related attributes and values (see Fig. 2). Thus, users' emotional responses are discovered from their interactions in a dynamic and non-intrusive way in order to improve recommendations regarding training courses. It is important to note that in many occasions users do not answer questions which produce lack of relevance feedback from the user side and the effect known as the sparsity problem in data. To reduce the dimensionality of the matrix generated we use Support Vector Machines (SVM). Then SVMs are used to classify and to predict users' behaviors from attributes which have a high impact on their emotional responses. Furthermore, SVMs have been used as a learning component in ranking users to assess their propensity to accept a recommended item.



(a) (b)

Fig. 3. Cumulative redemption curve (a) and Predictive Scores (b) for the increase in transactions of 1,340,432 users of emagister.com

Persuading Users through their Sensibilities

Outstanding salesmen use a different sales talk depending on the customer. Salesmen communicate a different message depending on customers' sensibilities, since if they catch their attention the sale is easier. What the *Messaging Agent* tries to do is to simulate this salesmen behavior.

Therefore, we generate a personalized message to each user following the next steps based on the users' sensibilities:

1. Select the product attributes to be used for the sales talk: depending on the features of the training course to sale, we select from the list of attributes the ones that can be used to sell the course.
2. Generate a message (sales talk) for each product attribute: this generation is carried out once and then is saved in a database of messages.
3. Assign a message to each user depending on his/her sensibilities: that is, the attributes of his/her user model that exceed a sensibility threshold. Then, we match these sensibilities with the attributes selected for the training course. In this moment, we can get three different cases:
    a. The user does not have any sensibilities for product attributes: a standard message is assigned to this user.
    b. The user has one of the product attributes as sensibilities: the message of this product attribute is assigned to the user automatically.
    c. The user has more than one of the product attributes as sensibilities: here we have two options:
        i. Order product attributes by priority and assign to the user the message of the attribute with most priority.
        ii. Assign to the user the message of the attribute that the user has most sensibility.

In this way the *Messaging Agent* sends different kind of messages for each user.

Results

We have tested SPA with eight Push and two newsletters campaigns. The target was 1,340,432 users in each campaign chosen in aleatory way. Our objective was to predict the users' propensity to do transactions (i.e. actions such as click streams, information requirement about training courses, enrollments, opinions, etc.) in Push and newsletter communications. Thus, SPA delivered more empathic recommendations through two well differenced functions:

1. The recommendation function: to send in an individualized manner the action with most probabilities of execution by the user.
2. The selection function: to choose the user with greater propensity to follow a course in the recommender system.

Both functions are based on attributes which have high impacts on users' emotional sensibility to predict their behaviors.

Fig. 3 shows successful results obtained with our predictive models tested with a target group of users in the overall set of ten campaigns. Particularly, Fig. 3(a) shows that with the 40% of commercial action (i.e. the effort to send Push and newsletters), SPA achieves more than 76% of useful impacts.

So, we have improved the redemption of Push and newsletters campaigns in a 90%. On the other hand, Fig. 3(b) shows the predictive scores of the total set of ten Push and newsletters campaigns. So, SPA achieves an average performance of 21%, it means 282,938 useful impacts.

Lessons Learned

In this work a domain with high level of collaboration was used to test SPA. We are aware that SPA is more appropriate for companies that can acquire user's implicit feedback through a rich interaction through highly dynamic environments. For instance, networked games and leisure (e.g. music and tourism recommender systems) are potential application domains for SPA. The question however remains open for domains where the user is not willing to collaborate with the system. In this sense, acquiring relevant information to keep user's preferences up-to-date is crucial in order to close the cycle of recommendations and to obtain successfully results using SPA. From our experience, we have learned that SPA is particularly suitable for domains where users perceive that the value of the information delivered from company/system side is higher than the value of the information delivered from their side. Instances of this kind of systems are social software systems which organize contextual information about user activities and tasks in all spheres of information (i.e. at home, at work, travels, relationships and shared interests, among others).

Conclusions and Future Work

SPA is smart adaptive system based on the integration of intelligent agents with adaptive and incremental learning capabilities to embed the user's emotional intelligence in recommender systems. It was developed through a multi-disciplinary approach inspired in future emerging recommender systems in Ambient Intelligence scenarios.

Along these lines, we have suggested a shift in the way that research community on recommender systems could direct efforts to build more intuitive and sensitive systems. SPA is the first software tool created in its category that embeds users' emotional information to enrich recommendations in every day life.

SPA also reports several business benefits for enterprises interested in discovering users' emotional sensibilities associated to their services and products. SPA has high performance pre-processing proactively LifeLogs of millions of customers. SPA also includes smart behavior in its user models reducing dramatically the total cost of ownership. Finally, SPA is able to generate individualized messages for each customer according to his/her life cycles during the purchase processes.

A related ongoing research in which SPA is being used is the Intelligent Citizen Attention Service project (iSAC) deployed in the Terrassa City Council (Spain) (iSAC 2006). We are using our approach to improve the citizen's experience and personalize the information based on the current citizen's needs and context.

In further work, we will improve SPA with unobtrusive methods of acquisition of user's relevant feedback in real time through wearable computing. Currently, we are sensing physiological and contextual parameters of players in networked gaming experiences because the quality of a game is related to its capability to cause emotions in the player to provide an estimated emotional state that works as a driving element for the game plot. These experiments are being carried out with the SPA platform mapping physiological signals to user's emotional context.

Acknowledgments

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