Recommender Systems supporting Decision Making through Analysis of User Emotions and Personality

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Abstract. The influence of emotions in decision making is a popular research topic in psychology and cognitive studies. A person facing a choosing problem has to consider different solutions and take a decision. During this process several elements influence the reasoning, some of them are rational, others are irrational, such as emotions. Recommender Systems can be used to support decision making by narrowing the space of options. Typically they do not consider irrational elements during the computational process, but recent studies show that accuracy of suggestions improves whether user's emotional state is included in the recommendation process. In this paper we propose the idea of defining a framework for an Emotion-Aware Recommender System. The user emotions will be formalized in an affective user profile which can act as an emotional computational model. The Recommender System will use the affective profile integrated with case base reasoning to compute recommendations.

Keywords: Emotions, Recommender Systems, Human Decion Making

1 Background and Motivation

Emotions are an important aspect of our life. They have a regulatory affect on everyday task and heavy influence each decision that we take. Low intensity emotions have a positive advice role [5], while high intensity emotions can be a potential source of biases for a clear and logical reasoning [4]. When users do not have a complete knowledge of the domain, and the decision can produce risky consequences, negative and intensive emotions like fear and sadness can narrow attention and generate less consciousness decision [7]. A system that supports decision making has to adapt its behaviour according to the roles and the types of the emotions that users feel during the decision task. Recommender Systems (RSs) [11] are tools which implements information filtering strategies to deal with information overload and to support users into choosing tasks, by taking into account their preferences and contexts of choosing. RSs can adopt different filtering algorithms based on: the item content (description), the user activity, the knowledge of context, but usually they do not consider emotions and other irrational factors as features involved in the process that computes recommendations.

The research on emotion-aware RS is still at an early stage. Relevance of affect in RSs was discussed in the work by Zheng and Burke [21], that showed an increment of recommendation performance using emotions as a context in a context-aware RS. In this work, emotions play a minor role, because they are considered is the same way as other "rational" contextual features. Our work aims at defining a framework in which emotions play a more relevant role because they are *embedded* in the reasoning process. Another important work on this topic demonstrates how affective labelling of items can increases the performance of content-based RSs [20]. The work face with the problem of affective item modelling, while we would like to focus on modelling affective features of users. Anyway, literature on RS gives a positive valence to the possibility of including emotions in recommendation processes supporting decision making.
In our work, we focus on the following research questions:

1. Which techniques are most suitable to identify users' emotions from their behaviour?
2. How to define a computational model of personality and emotions for improving the user experience with recommender systems?
3. How to include the emotional computational model in a recommendation process?

For each research question we will propose some possible solutions, which are currently at a preliminary stage because the main author is in the first year of his doctoral program. As for emotion detection, we propose to use both explicit and implicit feedback strategies. Sentiment analysis techniques [14] will be adapted to infer the user affective state (emotions, mood) from the analysis of social network posts. Other implicit feedback techniques for the analysis of voice and biometric parameters will be also considered, as well as explicit feedback from questionnaires, like the Big Five Inventory questionnaire [12] to infer the user personality traits.

The idea is to collapse all the information acquired about the emotional state of the user and her personality into an affective profile which stores both rational and irrational data about user decisions. In other words, the affective profile is a knowledge base that allows the RS to reason about past user's choices, emotions felt during the decision process, contexts in which decisions were taken. The final goal is to define an Emotion-aware RS that will exploit case base reasoning [1] to solve new problems by adapting past solutions in similar context, and taking into account the emotional state of the user, as well as personality traits.

2 Emotion Detection Strategies

In the decision making literature, the decision task is influenced by expected emotions and immediate emotions. Expected emotions are affects that the user suppose to prove as a consequence of the decision. Immediate emotions are consequence of an external event that has recently affected the user. Emotion-aware RSs have to identify immediate emotions and forecast expected emotions. The reasoning process should provide recommendations that generate positive expected emotions for a specific user in a defined immediate emotional state. Emotions during the decision process can be detected using implicit or explicit strategies. Explicit strategies are based on method that interacts directly with the user asking her which emotion is felt at the decision time. Questionnaires can be used to identify both user personality traits and user emotions. The 44-items Big Five Inventory questionnaire [12] can be used to infer the user personality traits among the dimensions: Openness to experience, Conscientiousness, Extroversion, Agreeableness, Neuroticism. Often people are not able to explicate correctly emotions, and explicit strategies could not be enough to correct identify immediate emotions. For this reason, implicit strategies can be adopted. Tkalcic[19] shows that emotions can be detected from videos, but with limited accuracy. Poria [15] present a multi-modal framework that uses audio, video and text sources to identify user emotions and to map them into the Ekman's six emotions [6]. The results show that hight precision can be achieved in the emotion detection task by combining different signals. According to this work, an useful implicit source that can be used to obtain immediate emotions informations is the text, and particularly posts gathered from user's Social Network activities. Research on this topic showed that both user personality traits [10, 8] and user emotional state [17, 13] can be inferred by adopting NLP techniques. Machine learning techniques have been also used for this purpose: one of the most useful framework adopted is SNoW, a general purpose multi-class classifier [2]. Strategies based on emotion lexicon are also popular. They usually identify key terms in sentences and, then check the emotions associated with each word in an emotion-based lexicon [3]. In our proposal, we will evaluate different strategies for acquiring both emotions and personality traits.

3 Affective Profile and Recomendation Method

The user affective profile is an extension of the standard user profile used by RSs, usually a list of item with corresponding feedback given by the user. It will be used by the RS to adapt its computational process and to generate recommendations according to emotions. It integrates both rational and irrational elements: user personality traits (PT), historical decision cases (HC), contexts and user expertise (CE).

$$AP = PT \times HC \times CE \tag{1}$$

Personality Traits. Personality traits are formalized as a distribution of percent values among the dimensions: Openness to experience, Conscientiousness, Extroversion, Agreeableness, Neuroticism according to the Big Five model [9]. These elements are the distinctive traits of the user behaviour which allow to predict user common preferences and decisions. These are also important to define the affective features of the user.

Historical decision case. An historical decision case describes accurately the decision making task and emotions felt by the users. A case contains emotions felt during the decision process and the description of the decision task. The decision task can be divided in three stages [18]: early, consuming and exit. These emotions are formalized as a distribution of percent values among the six emotions of Ekman model[6]. During all the decision, strategies of emotion identification from video, audio source will be used. The process will be supported from strategies of emotion extracted from Social Network posts, while an additional emotional value could be gathered from user asking her the emotion felt at decision time. The description of the task is defined by: context of decision, problem, elements among which choosing must be performed, decision taken, feedback in a discrete scale from 1 to 10 to describe the utility of suggestions (1 means not useful, 10 means extremely useful). Future enrichment of these descriptions, including other emotional source are under evaluation.

Context and expertise. This is the rational part of the profile. The context is characterized by explicit features that describe user preferences in the domain. The expertise of a user in a specific domain is defined in terms of the number of decisions taken in that context.

The affective profile stores all the useful informations that RSs can use to adapt their behaviour according to the user affective description. Common RSs are based on an information filtering algorithm that do not consider user's irrational features such as emotions. An Emotion-Aware Recommender System takes as input information about context, immediate emotions and affective profile and generates a list of possible solutions of the problem, influenced by emotionally attributes. The reasoning strategy adopted is based on the emotional historical cases of the user collected in her affective profile. Case-based reasoning is the most appropriate strategy for considering user's rational preferences in a specific context, user's immediate emotions and user's past decisions. This is one of the most commonly adopted machine learning method, that exploits a knowledge-based representation of the context [1]. Case-Based Recommender Systems (CBR-RS) are specific RSs that adopt a representation of user preferences, historical cases and domain of decision to suggest solutions for a new problem, according to similarity to past cases.

The Emotion-Aware RS works similarly to a CBR-RS. In the first step, the recommender has to identify users similar to the active user (the one for which suggestion must be provided). Similarity measures, like cosine similarity, are used on vectors obtained combining personality features and preference features in the specific context. This set of users, including the active user, is used to identify decisions taken in the past. Each historical case have to match the problem, the active user immediate emotional state, and must have positive exit stage emotions (anticipated emotions) or positive user feedback. The matching of context and emotions will be computed using similarity strategies on their descriptive features. From the historical cases detected, candidate solutions are extracted and filtered or ranked according to the context of the problem. Then, an important task is to consider the influence of emotional features on the user based on the risk that the decision involves. Schlosser [16] describes the role of emotions in risky and uncertain domains. Immediate emotions influence the ability to consider all the relevant aspect of the decision, therefore they influence the quantity and quality of informations interpreted. Anticipated emotions influence the utility function of the decision. When users evaluate the consequences of the possible options, they will consider positive and negative anticipated emotions associated with them. For instance, a RS for financial investments must provide understandable and explicable solutions. It has to propose actions that will maximize positive expected emotions and minimize the diversification of the options. Emotions influence decisions also in a low-risk domains. As decisions in these domains are easy to revert, it is possible for the RS to suggest new and uncommon items, by diversifying recommendations according to preferences and emotional state of the user. An application that fall in this category is a music recommender system which can propose playlists according to the user mood and her tendency to maintain or change it based on her personality traits.

If poor data are available for the proposed computation pipeline, an inference from personality traits in the specific domain could be done to choose possible candidate solutions. For example, for people with an high value of "Openness", uncommon solutions can be selected as a candidate recommendations.

4 Final Remarks and Ongoing Work

Emotions are important elements of people's life. In each decision making task, emotions influence the choosing process. In those contexts where decisions lead to risky consequences, emotions need to be mitigated, while in others, such as music recommendation, they could be amplified and used to generate useful suggestions. Systems that support the decision making task, currently take into account emotions in a limited way, while we have proposed a solution able to embed emotions and personality traits into the recommendation process. The ideas proposed in this paper are currently developed within the doctoral program of the main author, therefore they are still at a preliminary stage.

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