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A Framework for Emotion-aware Recommender Systems supporting Decision Making

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Emotions influence everyday decisions. When people make decisions about movies to watch, songs to listen or even about more serious issues such as health, they perform a cognitive process that estimates which of various alternative choices would yield the most positive consequences. Indeed, this process in not totally rational because it is influenced, directly or in a subtle way by personality traits and emotions. In this paper we propose the idea of defining an affective user profile, which can act as a computational model of personality and emotions, included in a general, affective-aware, recommendation framework.

Keywords: Emotions, Personality traits, Recommender Systems, Human Decision Making

1. BACKGROUND AND MOTIVATION

The question of how to conceptualize emotions concerning their role in decision making (DM) has been deeply studied in the psychological literature over the last twenty years Pfister (1992, 2008); Loewenstein et al. (2003); Peters (2006); Fiori (2013). According to traditional approaches of behavioural decision making, choosing is seen as a rational cognitive process that estimates which of various alternative choices would yield the most positive consequences, which does not necessarily entail emotions. Emotions are considered as external forces influencing an otherwise non-emotional process (influence-on metaphor). Loewenstein et al. (2003) distinguish between two different ways in which emotions enter into decision making. The first influence is that of expected emotions, i.e. beliefs about the emotional consequences of the decision outcomes. Users might evaluate the consequences of the possible options by taking into account both positive and negative emotions associated with them and then select those actions that maximize positive emotions and minimize negative emotions. The other kind of affective influence on DM consists of immediate emotions that are experienced at the time of decision making. Such feelings often drive behaviour in directions that are different from those coming from the rational mental process and thus derived by a consequentiality evaluation of future consequences. Recommender Systems are tools that support users in the process of choosing options in several domains. These systems, usually implementing an information filtering algorithm based on user preferences, are starting to consider also affective information to adapt suggestions according to "emotional features" of users or items.

The positive influence of affects in recommender systems is shown by Zheng and Burke (2013) that got relevant results in terms of increased precision in Context-Aware Recommender Systems. Similar results are obtained by Tkalcic et al. (2013), that show an increase of performance in content-based recommender systems that use emotional item labelling.

In recommender systems literature, emotional feedback play different roles related to the acquisition of user preferences:

1. As a source of affective meta-data for item modelling and building a preference model;
2. As an implicit relevance feedback for assessing user satisfaction.

In this work, we focus on the first issue: the idea is to acquire affective features that might be exploited for user modelling. The aim is to define a general framework to include emotional aspects into a user profile augmented with affective features that can be exploited in the process of computing recommendations. In particular, we would like to design a novel, general recommendation process that takes into account both user personality traits and immediate emotions. For this purpose, three tasks must be performed:

1. Emotions identification;
2. Emotions formalization into the affective user profile;
3. Design of a recommendation process based on the affective user profile.

The work is still at an early stage and preliminary ideas will be discussed.

2. STRATEGIES TO IDENTIFY EMOTIONS

In Tkalcic et al. (2011), the authors show how it is possible to identify emotions during three different steps of the interaction between users and recommender systems. Following this structuring of user-system interaction, we will detect emotions in these different steps, using specific acquisition strategies:

1. Early stage: in this stage the user will face the decision task coming from an external context. The emotions which the user feels facing the problem will be detected. Those feelings are consequence of events not correlated to the decision, thus they should be found outside the recommendation process. For instance, they could be gathered from user's account on social networks like Facebook or Twitter. Daily posts will be analysed using sentiment analysis techniques to identify the user's affective state (e.g. mood) in the early stage of the decision task. Furthermore, A Big Five Inventory questionnaire proposed by John and Srivastava (1999) will be used to get the user personality traits (this could be done only once).
2. Consumption stage: during the decision task, the user will face with their expectation and their expected emotions after the decision. The current affective state could be acquired through explicit questions that allow the categorization of the current emotion among the six Ekman universal emotions Ekman (1993): happiness, sadness, surprise, fear, disgust, anger. Implicit affective feedback could be acquired by monitoring the user facial expression through specific tools for emotion detection.
3. Exit Stage: at the end of the decision task, consequence emotions will be available. Consequences could be immediate or postdated. If decision consequences are immediate, exit stage emotions will be gathered using the same techniques adopted during the consumption stage. An analysis of user's social network posts could be also performed to identify consequence emotions.

   The uthor identify two different main category of methods for gather emotions information: the explicit ask and implicit detection.

3. AFFECTIVE PROFILE

The user's emotions will be stored as components of her affective profile. Every decision taken using the system, will be stored formally to become an affective historical case for the specific domain. The history of the user decisions is the primary base of knowledge for a recommender system that must support the decision making task. This affective-augmented knowledge base allows to compute the user preferences with respect to an option, in a specific context, while it is affected by a well defined emotion. The affective profile is composed by user personality traits (PT), historical decision cases (HC), contexts and user expertise (CE).

$$AP = PT \times HC \times CE \qquad (1)$$

Personality Traits. Personality traits are formalized as a distribution of percentage values among the dimensions: Openness to experience, Conscientiousness, Extroversion, Agreeableness, Neuroticism in according to the Big Five model described by Goldberg (1990). These elements are the distinctive traits of the user behaviour which allow to predict user common preferences and decisions. A demonstration of these theories in a social network context is provided by Moore and McElroy (2012).

Historical decision cases. The historical case, stored in the user profile, is a formalization of the decision taken. It must describe accurately the decision task and emotions felt by the users.
The emotional state will be formalized as a distribution of the six Ekman emotions during the decision process. The task is defined by the context of decision, the faced problem, options to choose, decision taken, feedback in a scale from 1 to 10 to describe the utility of suggestions (1 not useful, 10 extremely useful).

Context and expertise. In these segment of the affect profile, all the contexts faced from the user are stored. For each context will be stored also the specific user preferences and skills to allow the recommender system to better understand the user's needs. We can formalize the expertise of each skill associating it with the number of decisions taken in this context.

4. EMOTION-AWARE RECOMMENDATION PROCESS

Recommender Systems (RSs) are largely used in a lot of different domains, from the classical e-commerce system to the more risky financial advisory domain. Commonly they are based on user's or item's descriptive features but they do not consider users irrational features such as emotions. An Emotion-Aware Recommender System takes as input information from the user affective profile and generates solutions to support the user in the decision task taking into account emotionally attributes. The recommendation strategy is base on the Case-based reasoning one of the most commonly adopted machine learning method, that exploits a knowledge-based representation of the context.

An Emotion-Aware Recommender System has, first, to use similarity measures to identify users that match the active user's affective profile. In particular they are used on vectors that includes user's personality features and preferences in the specific context. For each user identified, including the active user, are gathered historical cases that match the problem, the active user early stage emotional state, and positive exit stage emotions or positive user feedback. From the historical cases detected, candidate solutions are extracted and filtered or ranked according to the context of the problem. Using a preliminary week classification based on the level of risk of the decisions,three different macro contexts could be identified for our framework:

1. High risk domains: hard decisions are taken. In this context, it is important to provide appropriate and understandable (i.e. explainable) solutions. The important aspect to be taken into account is the correctness. An application that falls in this category is a recommender systems for financial investments. In this case, the RS could decide to mitigate the negative emotions felt by an inexperienced user by proposing low-risk investments.

2. Medium risk domains: decisions in these domains can hardly be reversed. An application that fall in this category is a RS for activity plans. In this context, there are some constraints that have to be satisfied, for example, work commitments.

3. Low risk domains: 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 playlist according to the user mood and her tendency to maintain or change it based on her personality traits.

The framework will be designed according to the described recommendation approach and macro-categoritazion of domains for the ranking of the solutions. When poor historical data are avaible, the described pipeline is not efficient. To supply the problem will be used strategies of inference of preferences from user's personality traits. For example, happy items will be suggested to users who have hight agreeableness value. An empirical demonstration of correlations between personality and user's preferences in a music domain is provided by Ferwerda (2015).

5. CONCLUDING 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 in which 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 framework 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 author, therefore they are still at a preliminary stage.

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