Personality and Emotions in Decision Making and Recommender Systems

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Abstract. In this paper we survey the work on the usage of personality and emotions in recommender systems. Recommender systems are designed to support humans making better decisions. It has been shown that personality and emotions account for the variance in human decision making. We present various models and acquisition methods for emotions and personality. Furthermore, we showcase examples of effective exploitation of personality and emotions in RS. We present in more details an example of the usage of emotions as implicit feedback for serendipitous recommendations.

Keywords: emotions, personality, decision making, recommender systems

1 Introduction

Recommender systems (RS) are being developed for assisting humans in making better decisions. Personality and emotions have been shown to account for individual differences in human decision making [5,12]. While personality describes enduring personal characteristics, emotions change very rapidly. In this paper we survey how personality and emotions have been used to improve RS.

2 Personality in RS

Personality accounts for individual differences among users. Several psychological models of personality have been developed. Among these, the Five Factor Model (FFM) [17] is the most widely used in RS [29]. The FFM is composed of five basic factors: *Openness*, *Conscientiousness*, *Extraversion*, *Agreeableness* and *Neuroticism*. These factors can be acquired explicitly (e.g. through questionnaires [10]) or implicitly (most commonly from social media [9,15]). In RS, personality has been successfully used to solve various problems. Including personality in user-similarity measures has helped alleviate the new-user problem [7,23]. The *Openness* factor has been proved useful to improve diversity [31]. Personality has also been found to correlate with music preferences [21]. Cross-domain recommendations have been tackled using personality [2]. It was also useful in group modeling for group RS [14,20]. Furthermore, it has also been used to model mood regulation music RS [8].

3 Emotions in RS

Unlike personality, emotions change more rapidly and are harder to model and capture. In RS, emotions are modeled either through the model of basic emotions (e.g. the six basic emotions *happiness, anger, fear, sadness, disgust* and *surprise* [6]), the dimensional model (i.e. the *valence, arousal* and *dominance* dimensions) or the circumplex model [22]. To acquire a user's emotion in a specific moment we can use either the intrusive questionnaire approach [1] or implicit methods developed in the affective community [11,28]. Emotions have been used in RS in various ways. The role of emotions in the content consumption chain differs in various stages [27]. Affective labeling has been used to improve recommendations [24,25]. The affective state of a user has been used as a contextual feature [13,32]. It has also been shown that personality relates to which emotions the users perceive in watching films [19]. A conversational RS used affective feedback in the form of the *hesitation* social signal [30].

4 Focus: Emotions as Implicit Feedback

Generally, in the RS literature emotional feedback is mainly associated with multimedia content and it is collected during or immediately after the item consumption. Spontaneous reactions to proposed items are collected with various aims, one of which is to exploit them as implicit feedback for assessing the user's satisfaction.

We argue that affective states derived from *facial expressions* could be particularly useful in situations where traditional performance measures are not sufficient to catch the perceived quality of suggestions with respect to the specific aspect being assessed. In particular, in [4] we addressed the research question: *Can emotions observed in facial expressions be considered as a trustworthy implicit feedback for assessing the effectiveness of suggestions produced by RS?* The investigation was focused on trying to establish/define a ground truth when evaluating the effectiveness of user-centric intelligent services like RS [3].

We started from the (quite obvious) observation that users do not need perfect rating predictions, but sensible recommendations. Thus, it is important to take into account factors, other than accuracy, which contribute to the perceived quality of recommendations. For example, serendipity of suggestions refers to the capability of providing the user with surprisingly interesting items she might not have discovered by herself. From this perspective, the effectiveness of recommendations depends on both attractiveness and unexpectedness of suggested items. While attractiveness is usually determined in terms of closeness to the user profile, the assessment of unexpectedness of recommendations is not immediate since it involves the evaluation of the emotional response of the user.

Thus, the problem of assessing the perceived quality of recommendations can be summarized by the following questions: *Can we recognize a sensible recommendation by reading the face of the users exposed to it? Can we read (on the face of the user) the pleasant surprise a sensible recommendation induces? Can we model the degree of serendipity conveyed by sensible recommendations by measuring the emotional response of the user?*

To this purpose, we designed a study with real users aiming at assessing the actual perception of serendipity of recommendations and their acceptance in terms of the widely adopted metrics of relevance and unexpectedness [18]. To measure the degree of satisfaction related to user experience and gather feedback in a movie recommendation scenario, we used both a questionnaire approach based on two simple binary questions (*"Did you know this movie?"* for assessing unexpectedness and *"Do you like this movie?"* for evaluating relevance) and an implicit affective labeling method implemented in Noldus' FaceReader™, a tool able to detect basic emotions [6] by analyzing videos that record users' facial expressions. Sensible recommendations were associated to the positive emotions of happiness and surprise.

The results of the experiment show an agreement between the explicit positive feedback acquired by means of the questionnaires and the implicit feedback gathered by means of the detection of happiness and surprise in users' facial expressions, thus revealing that emotions might help to assess the perception of effectiveness of RS as well as to contribute to the creation of a ground truth for the purpose of RS evaluation.

5 Future work

There are many open issues in the domain of personality- and affective-based RS. The lack of datasets is a problem that should be addressed (only a handful of these are currently available [15,16,26]). Furthermore, better implicit methods for the acquisition of personality and emotions should be developed. Personality and emotions play different roles at different stages of the process of selection and consumption of content. It is important to develop models, which use emotions and personality, that account for individual differences in the decision making as well as in the consumption and feedback stages of consumption to close the loop of personality and affective recommendations.

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