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PREFACE
Emotions and Personality in Personalized Systems

Introduction

Personality and emotions shape our daily lives by having a strong influence on our preferences, decisions and behaviour in general.
In recent years, emotions and personality have shown to play an important role in various aspects of adaptive systems, such as implicit feedback, contextual information, affective content labeling, affective e-learning.

In order to deliver personalized content, adaptive systems infer knowledge about the user through data mining algorithms that analyze the *digital traces* of the user. These information are used to build user models, representing preferences and behavior, which are exploited by personalization algorithms to select the content tailored to each user in a given situation.

The advances in personalization technologies reduced the distance between these systems and the user, starting to incorporate more and more psychologically motivated user-centric concepts, such as personality [7] and emotions [22], to model their preferences and attitudes. In order to achieve true emotion- and personality-aware personalized systems, psychological theories and computational models need to become a part of user models and personalization algorithms.
The question of how to conceptualize emotions concerning their role in human decision making has been deeply studied in the psychological literature over the last twenty years [6,10,13,14,15].

According to traditional approaches of behavioral 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). Some context-aware recommender systems are adopting algorithms that follow this metaphor, modeling emotions as contextual factors [12].

A new vision about the classical influence-on metaphor has been proposed in [15]: emotions do not simply influence a purely rational process, but they are virtually part of any decision making process. Therefore, authors started to follow an alternative approach consisting in adopting a computational model of emotions that drives the recommendation process [16].
Personality also plays an important role in decision making [5]. From its definition in psychology, personality accounts for the individual differences in our long-term emotional, interpersonal, experiential, attitudinal and motivational styles.

Several studies have shown that personality traits influence user choices, therefore including a model of personality of the user is a natural choice for delivering personalized recommendations or adaptive services [23]. The most commonly adopted model is the Five Factor Model (FFM), which describes personality traits by means of five factors: openness, conscientiousness, extraversion, agreeableness and neuroticism [11]. In [23], the authors analyze several scenarios where personality traits have shown to be useful to improve personalized systems, in particular recommender systems. More details are provided in the following section.

Exploitation of Personality and Emotions for User Modeling

In personalized systems literature, emotional feedback is mainly associated with multimedia content [19,20,22,24] and play different roles related to the acquisition of user preferences:

1) as a source of affective metadata for item modeling and building a preference model;

2) as an implicit relevance feedback for assessing user's satisfaction;

As for the first issue, the idea is to acquire affective features that are included in the item profile and might be exploited for user modeling. In [24] a feature vector is acquired, that represent the valence, arousal and dominance dimensions (identified by Russell [18]) of the emotive response of a user to an item; then the user model is inferred by machine learning algorithms trained on the item profiles and the explicit ratings given to the consumed items. The detected emotion can be used in two ways: item categorization (the item is funny because it induces happiness in most of the users) and to model individual users (the user *u* likes items that induce sadness). In [9], a probabilistic emotion recognition algorithm based on facial expressions was employed to detect emotions of users watching video clips. The level of expressed emotions associated with items were used as features to detect personal highlights in the videos.

The main issue that these and other similar studies addressed [25] is the identification of a valid set of affective features that allows the definition of an effective user model for the canonical (relevant/non-relevant) item categorization. The main challenge from both a user modeling and decision making perspective is how to represent the whole affective state of the user in terms of emotions, mood, and personality.

As for the second issue, the main motivation for assessing user's relevance by means of emotions detection techniques is that, since satisfaction is an internal mental state, techniques that can disclose feelings without any bias are expected to be a reliable source of implicit feedback. In fact, the emotional response is hardly alterable by the user. Furthermore, face detection is unobtrusive because usually the user is monitored by a camera, and then recorded videos are analyzed by a facial expression recognition system. Pioneer studies on this topic are those made by Arapakis et al. [1,2,3]. They introduced a method to assess the topical relevance of videos in accordance to a given query using facial expressions showing users' satisfaction or dissatisfaction. Based on facial expressions recognition techniques, basic emotions were detected and compared with the ground truth. They investigated also the feasibility of using reactions derived from both facial expressions and physiological signals as implicit indicators of topical relevance.

In [4] implicit emotional feedback is exploited to assess the serendipity of recommendations (i.e. unexpected recommendations liked by users). A user study was

performed to assess both (i) the acceptance and the actual perception of serendipity of recommendations, through the administration of questionnaires and (ii) the analysis of users' emotions detected from a face recognition software, respectively.
The results showed that serendipity is often revealed by the presence of positive emotions, such as happiness and surprise.

Personality traits have been exploited by recommender systems in different scenarios [23]. Personality is suitable to address the new-user problem. A commonly adopted approach is to compute similarity among users in collaborative filtering, based on similarity of their FFM models [8]. Another interesting application is the computation of a recommendation list with serendipitous items: personality can help to personalize the level of unexpectedness of items in the list according to the individual aptitude of users towards diversity preferences [21]. Furthermore, personality is an important factor in group dynamics, therefore knowledge about user personality traits can help group recommendation. In [17] the authors adopt a conflict personality model to describe the relationships between group members in a movie recommendation context. The variety of domains in which personality and emotions are exploited to deliver personalized services is also shown by the three papers accepted for this focus section.

Contributions of this focus section

The paper "Model of Personal Discount Sensitivity in Recommender Systems" is an extended version of the work presented at the Third Workshop on Emotions and Personality in Personalized Systems, held in conjunction with the ACM Conference on Recommender System (2015). The authors present a matrix-factorization based recommender system that incorporates discount sensitivity in the model. Bayesian Personalized Ranking is extended with a matrix factorization approach in which items evaluations come from item preference, as well as preference for discount, which is considered a *domain-specific personality trait*.

The paper "Step Towards a Model to Bridge the Gap between Personality Traits and Collaborative Learning Roles" investigate the impact of personality on learners' roles for group formation. They first match the personality trait introvert/extrovert to anchored instructor or problem holder roles according to collaborative learning theories, and then represent the new roles in a collaborative ontological structure. A case study they showed that unsociable characteristic (i.e., introverted) tends to negatively influence students' performance in the group work.

In the last paper in the focus section, "Using Player Type Models for Personalized Game Design – An Empirical Investigation", the authors propose an investigation about the impact of different player type models on the player's experience. In particular, the authors conduct a statistical study to assess whether personalization of a mobile game according to specific player models (Mastermid, Seeker) could effectively improve game experience. A study revealed that the player models cannot predict player experience on personalized missions.

In general, from all the papers accepted for the focus section, it emerged that emotions and personality are clearly confirmed as user-centric aspects of personalization in several areas, from marketing to e-learning.

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