The influence of user's emotions in recommender systems for decision making processes

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Abstract. The decision making process is a very hard task to face, because a lot of external elements could influence the final decision taken. The paper will present the influences of emotions and personality in this task and will propose a recommender system able to take them in accounts during the recommendation process.

Keywords: Emotions, Recommender Systems, Human Decion Making

1 Introduction

People have to take decisions, about tasks they have to carry out, everyday. Sometimes, decisions are easy to be taken because the context is usual or the generated consequences are not crucial. Other times, decisions are very difficult to be managed and emotions like fear, sadness or surprise will influence negatively the logical reasoning. Emotions play a cardinal role in the decision making task [1] and their influences should be taken into account during the recommendation process to propose solutions that could improve the positive emotional state of the user.
Traditional recommender systems do not include emotions in the computational process and only recently some works have explained how is possible recognizing personality and emotions from different sources and apply them. Gosling shows how to extract the personality profile from Facebook [2], and Golbeck uses Twitter for the same task [3]. The authors describe how to adapt the recommender output to the user personality profile but they do not consider emotions. Tkalcic[5], suggests using emotions in different stages of recommendation process but how changing the process in each stage is an open issue.
An user is very influenced by incidental emotions [4] and by expected consequences that the decision will produce on the future emotional state when he faces a new and relevant decision task. A recommender system should recognize this emotion, and should adapt, starting from user preferences and user personality traits, the recommendation output in according to the user emotions to help her taking a clear and a pondered decision.

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This early stage work, supervised by Marco de Gemmis [1] , proposes a strategy to consider emotions in the recommendation process. The main research topic that we will investigate are:

1. Contextualization of emotional and personality traits that influence the decision task;
2. Definition of a computational emotions model useful for recommender systems;
3. Identification of emotional source to use during the recommendation process;
4. Study of innovative recommender system models based on emotional profiles.

Later in the document we describe the preliminary idea and how the future results will contribute to improve the current recommender systems state of the art.

2 Related Works

Emotions have been studied ample in the psychological and cognition areas. The first fundamental study was conducted by Darwin[12], who supposes that emotions are universal in according to their origin of the species theory. Ekman [8] influenced by Darwin, identifies six universal emotions (happiness, sadness, surprise, fear, disgust and anger) and their respective facial micro expression. This classification is used largely in different domains, and their experimental results are fundamental for the emotion recognition task of this work.
Important studies in psychology about the influence of emotions in a decision making task are available. Norbert Schwarz [10], provides a selected discussion about emotion, cognition and decision. The author recaps fundamental concepts to consider while people face with the decision making task, that is post decision affects, anticipated affects and memories of past affects. This concepts are largely used in this work.
The interest of the research about the use of emotions in computer science is more recent, particularly in recommender systems area. Zheng and Burke [11] demonstrate how emotions are relevant in the context-aware recommender systems, analogous results were obtained from Tkalcic[6] that demonstrates how affective labelling increases the performances of content base recommender systems. This results show that taking into account emotions in recommender systems, generates benefits. In according to this we will work on this area to contribute to generate relevant results for the topic.

3 Approach

The main objective of the work is to define a framework that includes the emotional aspects into recommender systems, and particularly in which that support

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the decision making process. The work is in an early stage, and more studies and in-depth analysis will be conducted. To solve the proposed problem, we decided to face it identifying sub-tasks that focus on different aspects.
First, we will focus on defining an emotional model for identifying, formalizing and classifying user emotions. Consequently we will define an user emotional profile that includes informations to be used in recommender systems. Finally, we will identify behaviours of the recommender systems in according to the defined emotion profile.

4 Identification of Emotions

Emotions are fundamental elements of the cognitive research area and a great deal of models has been prosed. We adopt the Ekman model [8] of emotion because the low number of primary emotions defined in it supports the combination of different strategies of emotions identification.
These strategies can be implicitely or explicitely. The explicit strategy is invasive because the system will ask users about emotions that they feel. The elicitation of emotions is not an easy task. People, often, do not really know what they really feel. Questionnaires for deducing emotions and personality traits could be adopted [14]. The implicit strategies are not invasive because all the collected data do not influence the natural behaviours of the user, but they are affected by a lot of imprecisions in spontaneous context [7].
We will detect affects in three different stages of user computer interaction and in each one we will use a specific type of emotion identification strategy in according to Tkalcic's [5] work.

1. Early stage: incidental affects will be detected analysing latest daily posts on Facebook and Twitter. Techniques of Natural Language Processing (NLP) will be used to make a quickly emotional analysis of the latest user's shares.
2. Consumption stage: expected consequences of the decision will generate evident emotions. Will be used techniques of on-line video analysis combined with an explicit question about emotion can generate an accurate emotionally user profile. We will obtain a single value from a questionnaire and a distribution of percentage value among the six basic emotions from the video analysis. In this stage user emotion profile will be extended with information obtained by a proposed 44-items Big Five Inventory questionnaire[14]. This questionnaire will be proposed only the first time that the system will interact with the user.
3. Exit Stage: after the decision, the consequential emotion will be generated. This step is used to get a feedback from the user about the decision taken. If consequences of decision are not immediate, an analysis of social network posts, using the same techniques adopted in early stage emotion identification, will be done when consequences will occur.

Using Social Networks posts it is possible to identify user personality traits [2, 3] and user emotional state [13, 20] adopting strategies of Natural Language

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Processing. Several strategies are adopted in machine learning literatures for this task and one of the most useful framework adopted is SNoW, a general purpose multi-class classifier [22]. Strategies based on emotion lexicon are also popular. A general strategy that use this resource, first, identifies key terms of the sentence and, later, checks the emotions associated to each world in a emotion based lexicon [23]. The specific algorithms of NLP, the questionnaires to propose to the user and framework of video-audio analysis to adopt are object of evaluations

The specific algorithms of NLP, the questionnaires to provide and framework of video analysis to adopt are not currently decided.

5 Affective profile

The user emotions gathered during the decision making are formalized and stored in an effective user profile. The profile will be used by the recommender system to adapt its computational process and to generate recommendations in according to emotions. It is composed by different 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 in according to the Big Five model [15].

Historical decision case. An historical decision case describes accurately the decision making task and emotions felt by the users. A case contains early stage emotions, consuming stage emotions, exit stage emotions, and a description of the task.
Early stage emotions in according to the description before provided, are formalized as a distribution of percent values among the six emotions of Ekman model[8] gathered from social networks posts. The same formalization is used for the consuming stage and exit stage emotions. In the consumption stage emotions is gathered an additional value from user asking the emotion she felt. The description of the task is defined by: context of decision, problem, elements among which choosing, decision taken, explicating feedbacks in a scale from 1 to 10 to describe the utility of suggestions (1 not useful, 10 extremely useful). The historical case could be enriched with more features, for example a description of interaction between user and system, but we decide to simplify the situation for realizing a preliminary working framework.

Context and expertise. The context is characterized by explicit features that describe user preferences in this domain. The expertise of user in the specific domain is the number of decisions taken in this context, starting from an initial value obtained from a user ability questionnaire. The available contexts of applications will be defined a priori in a list of chooses because we do not focus on the context detection strategies.

Memory of the past affect Each time that the user will take a decision, interacting with the system, her affective profile increases and new emotionally historical cases will be added. Some cases are more important than others because they generate negative emotions that influence future user decisions in the same domain more than a positive emotion. This effect is called memory of the past affect and it is well described by LeDoux [16].This effect will be considered in the framework to provide, in this particular case, only solutions that generate positive emotions to increase the initial user mistrusts.

6 Emotions and Recommender Systems

Recommender Systems (RSs) are largely used in a lot of different domains, from the classical e-commerce system to the more difficult and risky financial advisory domain. An important application of them is in the decision making process. When people have to take a decision, they have to analyse the situation and to take a logical choose among different options. A RS can support this task, proposing solutions in according to user necessity, for example, obtaining them from similar users decisions. In contexts where it is important making logical decisions, proposed solutions have to be full demonstrable, because a motivation of the process used to select each proposal have to be provided. A recommender system have to adopt different behaviours in according to the context of decision to provide suitable recommendations. We identify three different kinds of contexts varying the risk value among hight, median and low in according to the risky consequence that the decision could generate. A decision is risky if it heavily influence user common behaviours and user has low experience in the domain. For example decisions about money or health can be risky decisions.

1. High risk: they are decisions hard to be taken. In this context it is important providing correct and demonstrable solutions. The core aspect to be taken into account is the correctness. An application that occurs in this context is a recommender systems for health wellness.
2. Medium risk: they are decisions that influence behaviours momently without the possibility to revert them. An application that occurs in this context is a recommender systems for fashion shopping.
3. Low risk: they are decisions that the user makes commonly and that are easy to revert. Working on this context allows to suggest new and uncommon elements diversifying users decisions. An application that occurs in this context is a music recommender system.

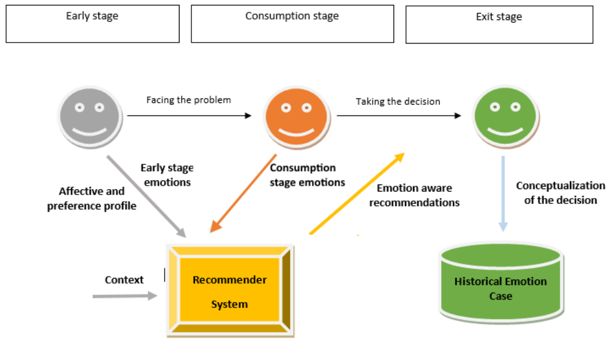

Fig. 1. A general work-flow of recommendation process that includes affective profile

Using this definitions of context, it is possible to define a general framework for recommender systems able to include emotions in the recommendation process (Fig. 1). The Emotion Aware Recommender System, starts the recommendation process from personality traits. Users with similar personality and explicit preferences in same contexts, are detected using common similarity measures, for example a cosine similarity on vector obtained combining profile features and preference features. The system uses this set of users to identify decisions taken in the past for the considered problem. This set of solutions have to be taken in same emotional state of the considered user and, it has positive exit stage emotion or explicit positive feedback of utility. This solutions will be filtered or ranked in according to specific recommendation process influenced by the application context. The output generated is a list of possible solutions to the problem influenced by emotionally attribute. During the three stages of the process, emotions are identified in according to the process described previously. All the informations about the decision taken will be stored inside an historical emotion case that will update the user affective profile. The described recommendation strategy is base on the Case-based reasoning [21] one of the most commonly adopted machine learning method, that exploits a knowledge-based representation of the context. The formalization of the computational process of recommender system that face emotions into different contexts, is today being studied, but some preliminary ideas will be provided.
If not enough data will be available for this computation, an inference based only from personality traits in the specific domain will be done, but this task is now an open issue of the work.

6.1 Recommendation process in hight risk context

The recommendations about decisions that will generate risky consequence have to be accurate and demonstrable. For this kind of tasks, a rule base system could be a good solutions. The knowledge about domain could be fully encoded and combined with specific rules that consider emotions. A demonstration of the proposed elements could be always provided. A set of possible general rules about early stage emotions, is provided.

1. Happiness and Neutral: the user is relaxed and used to face the problem [18]. The system has to maximize user profit. Users historical solutions can be included, if possible. It is possible to diversifier solutions between low and hight probability to produce negative consequences.
2. Sadness and Anger: the user is not fully concentrated [17] on the task. The system has to prefer a good agreement between user profit and low probability to generate negative consequence. If successful historical user cases are presents, they could be adopted refining the proposed solution.
3. Surprise, fear and disgust: the user maybe does not have enough expertise to take a safe and accurate decision. The system has to fully describe each solution provided and to propose an element with low probability to generate negative consequence.

If a large number of negative affect memories is present in the user history, the system has to increase the confidence with the user providing only solutions that certainly produce positive emotions. A formalization of presented rules will be realized later in research.

6.2 Recommendation process in medium risk context

Medium risk decisions provide more degree of freedom than risky decisions, because it is not mandatory to provide a demonstration of the solutions. It is possible to mediate recommendations providing items that strongly meets user preferences and also items that are in according to user emotions. A description of pros and cons of each proposed solution could be useful to support the user decision.

6.3 Recommendation process in low risk context

Emotions play a relevant role in low risk contexts [9] because decisions are often taken without a long and logical reasoning. Incidental emotions influence intensively the decision making task and people take decisions in according to them. Each person has different behaviours in this situation, for example some people like listening sad jazz music, others like happy jazz music and other ones generic rock music when they are sad. In this context recommendations are based on the user historical cases and the similar users decisions in the same emotionally state. Particularly, if the user is in an happiness state, an intensive diversification of results could be done, trying to generate serendipity. If historical cases are not available, it is possible to consider the possibility of import user emotionally preference from correlated similar domains. For example the study of Cantador[19] demonstrates how it is possible to extend books preferences in music or film domain.

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7 Conclusions and future work

Emotions are important elements of people's life. In each decision making task, emotions influence the final option choose. In contexts that generate riskly consequence they need to be mitigated, in others, for example music domains, they can be amplified and used to generate useful suggests. Systems that support the decision making task, currently do not consider properly emotions, for this reason, we have proposed a framework able to include emotions inside recommender system process. It could be used to produce recommendations in according to the user preferences, personality and emotional state. The ideas proposed in this paper are consequences of a preliminary work on the topic that need more studies and empirical experiments to formalize them. Open issues are presents and a lot of elements need clarifications but this overview could provide useful global schema for a future complete work.

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