Personality-Based Recommendation in E-Commerce

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Abstract. In recent years there has been an exponential increase in the number of users each day adopting e-commerce as a purchasing vehicle of products and services. This has led to a growing interest from the scientific community in approaches and models that would improve the customer experience. Specifically, it has been repeatedly pointed out that the definition of a customer experience tailored to the user personality traits would likely increase the probability of purchase. In this article we illustrate a recommender system for e-commerce capable of adapting the product and service offer according to not only the user interests and preferences, and his context of use, but also his personality profile derived from information relating to his professional activities.

Keywords: Personality-based, user model, context-awareness, recommender system, e-commerce

1 Introduction

In literature there are several works that describe how the definition of a customer experience taking into account the user personality ensures the increase of the purchase probability. The study described in [11] shows the correlations among the reasons that lead a user to buy and the way in which he makes the purchase. In particular, it describes how a user driven by utilitarian reasons prefers making a "goal-oriented" research, since he has already a purchase plan, and the search has the only aim to obtain information about the product to be purchased, its cost, convenience, and availability. Another, different situation, is when the reasons that lead the user are of a hedonistic nature [1]. In such a case the user usually adopts an "exploration-oriented" search, in which he has no purchase plan yet, but he makes it by browsing and exploring different solutions. To et al. in [12] point out how the motivations that drive a user to purchase are related to personal traits distinguishing him; specifically, this study suggests a possible relationship among a theoretical personality model, such as BIG FIVE [6], and hedonistic and utilitarian motivations. Such models require the extraction of information needed for defining the user personality. For example, in literature there are several questionnaires [3], whose compilation allows us to extrapolate the user BIG FIVE profile. Unfortunately, this approach is not applicable to the e-commerce context, since the length of these questionnaires is not negligible and from the consumer point of view its purpose is not of immediate identification, so both the number of users, and the attention devoted to their compilation, will be reduced. To this end, it is appropriate to investigate different approaches to the identification of the user personality traits. The analysis of the literature has revealed the possibility of identifying the user personality from information on his profession. In particular, the theoretical personality model RIASEC [4] can be used for this purpose. Its name is an acronym of the six following personality traits: Realistic, Investigative, Artistic, Social, Enterprising, and Conventional. Hence, it is possible to associate any single profession with some personality traits of the RIASEC model. For example, a person practicing management accounting is associated with an IEC (i.e., Investigative, Enterprising, and Conventional) personality profile, which corresponds to a mainly investigative person having a good aptitude for business and repetitive activities. In this scenario, the user explicitly declares his profession, from which his personality traits are derived according to the RIASEC model.

In this article we propose a context-aware recommender system that suggests products and services in the e-commerce domain. During the recommendation process, our approach is capable of taking into account not only the user interests and preferences, but also his personality profile. For this purpose, the system makes use of a neural network whose input is the user personality profile according to the RIASEC model and output are the weights to be used in the combination of the results coming from the different modules of the system. The main goal of this process is to adapt the type of research of products and services available within the e-commerce platform to the user personality profile and, hence, to the motivations that lead him to the purchase.

2 Related Work

Recently, studies have indicated that there is a significant connection between personality and people tastes and interests [5]. Studies also show that personalities influence human decision making process and interests [9]. By drawing on the inherent inter-related patterns among users personalities and their interests/behaviors, personality-based recommenders are designed to provide personalized services. Several studies deal with the correspondence among characteristics of the personality and purchase intentions of an individual. Holland's theory (RIASEC), unlike the others, describes the strong connection between the environment and the individual personality: the latter is manifested through preferences for professional occupations and, at the same time, work environments are shaped by people working in them and what they do [4]. The user decisions are influenced emotionally, at least partially, by which content to choose, because while using applications with recommender systems he is constantly receiving various stimuli (e.g. visual, auditory) that induce emotional states. Thus it is important for the recommender system application to detect and make good use of emotional information. During the user interaction with a recommender system and the content consumption, emotions play different roles in different stages of the process. In [10] the authors subdivide the user interaction process in three stages, based on the role that emotions play: (i) the entry stage, (ii) the consumption stage, and (iii) the exit stage. Nunes and Hu [7] propose a personality-based recommender system to provide a better personalized environment for the customer. They claim that one interesting outcome of introducing a psychological dimension into the recommender system could be the possibility of products categorization based not only on their attributes (price, physical parameters, etc.), but also on the effect they may have on the consumer. Affective content profiling is still an open question, especially profiling content items that last longer than a single emotional response. Other studies put the attention on the context-aware recommender systems which help users and their desired content in a reasonable time, by exploiting the pieces of information that describe the situation in which users will consume the items [8].

3 The Proposed Approach

The proposed user model is based on the Vector Space Model technique to represent information about users and resources, namely, products and services. With this approach we define a *Concept Space* that models the knowledge base of interest with a conceptual subdivision (ontological) in R^d, with d number of ontological classes. Within this space, users and resources are represented by a *Concept Vector*, a weighted vector structure whose weights are, for resources, the level of consistency with concepts representing space and, for users, the levels of interest in the specific concepts of the knowledge domain. In the first case, a domain expert builds the vector that models the service, in the second case, the Concept Vector describes the user profile ($V_U \in R^d$) constructed and updated in function of the information related to his actions to represent the real and current interests of the consumer. Such information may be collected in explicit form, for example by completing a questionnaire, or in implicit form, through the use of implicit feedback techniques that, from user activities (e.g., purchases, queries, clicks) are able to extract information related to his interests and habits. The user action modeling and consequent user profile update occur in two distinct phases. The first, named *Concept Extraction*, builds a Concept Vector for every single user action A made by the user U ($V_{U,A} \in R^d$). The user profile update in function of his actions can be done after modeling user behavior. This phase, named *Concept Aggregation*, takes advantage of the Rocchio's algorithm to combine two vector structures ($V_{U,A}, V_U \in R^d$), thus obtaining the updated user profile ($V_U \in R^d$):

$$V_U = \alpha V_U + \beta \frac{1}{|V_{U,A}|} \sum V_{U,A}$$

The coefficients α and β represent the weights associated to the vectors $V_{U,A}$ and V_U, and they can be experimentally obtained through a preliminary testing on a small number of users. It is reasonable to expect that weights associated with explicit feedbacks are higher than those associated with implicit feedbacks. Indeed, in the latter there is likely to be a noise component due to the potential misinterpretation of the user actions. Modeling the user profile and electronic services through vector structures allows us to define a third phase, called *Concept Matching*, to propose the services of potential interest for the consumer. The Concept Matching is based on the comparison among the user profile and available resources modeled in the knowledge base. In particular, it is possible to filter the services obtained through the search activities by comparing them with the user profile characteristics. In this case, it is possible to compute the scoring value that represents the affinity level between each service and the user profile by means of the cosine similarity rule:

$$\text{Scoring} = \frac{V_U \times V_O}{\|V_U\| \|V_O\|}$$

Such value allows us to re-rank or, alternatively, filter, the search results. Thus it is possible to suggest personalized services or products of potential interest for a specific consumer.

3.1 Contextual Model

Current mobile devices enable users to interact with e-commerce services in multiple contexts (e.g., while traveling or in a shopping mall). Therefore, it is interesting and effective to monitor the contextual dimension that occurs during the interaction with the system in order to determine any correlations that may be useful during the product and service recommendation. In order to associate the current context with the content available on the e-commerce platform, a subset of features that can be measured on current mobile devices (e.g., smartphones, tablets) have to be initially identified. With a view to obtain a matching among the current context and the elements of the e-commerce service that may be of interest to the user, a domain expert has to identify all the features of a specific item that can be influenced by this context. The expert encodes such information in vector terms, where each dimension can take a value in a real interval (e.g., relative distance), or in a finite set of elements (e.g., "purchasable during the summer" in $\{$true, false$\}$). The V_C contextual vector is thus compared with the vector representing the domain elements identified by the expert. The matching process consists in the following steps:

1. the system identifies a first list of N results through the Concept Matching procedure in combination with a metric based on the user location;
2. each one of the N elements retrieved in the previous step is associated with the V_O vector and the V_C contextual vector is combined with each of them;
3. by means of a decision analysis algorithm based on Decision Trees, a value is computed for each of N elements, which expresses the relevance of the element as to the current context;

4. the list of N elements retrieved at the first step is re-ranked based on the relevance value of each element.

3.2 Search Results Combination

Now we can consider three lists of results: (1) the first list is obtained through a traditional matching process among the user query and available resources indexed by name and description. Such a matching process relies on traditional Information Retrieval techniques. The output corresponds to a R subset of resources; (2) the second list can be obtained through the Concept Matching process described above, that is based on the comparison among the user profile and available resources; (3) the third list is given as output of the contextual module. Subsequently, a combination of the three results lists can be performed. In other terms, the score associated with each element belonging to the R subset and obtained through the filtering is combined with the scores related to the matching with the user profile and the contextualization module. The three weights to be associated with the scores can be obtained as output of a neural network (see Figure 1), whose input is the user personality profile according to the RIASEC model. Specifically, a feed forward multi-layer perceptron can be employed for this purpose. The training data can be extracted from implicit and explicit feedbacks provided by users. A recent experimental prototype employed in artificial and real settings, and based on these technologies, has proven effective in the particular context of the recommendation of points of interest (e.g., restaurants) [2].

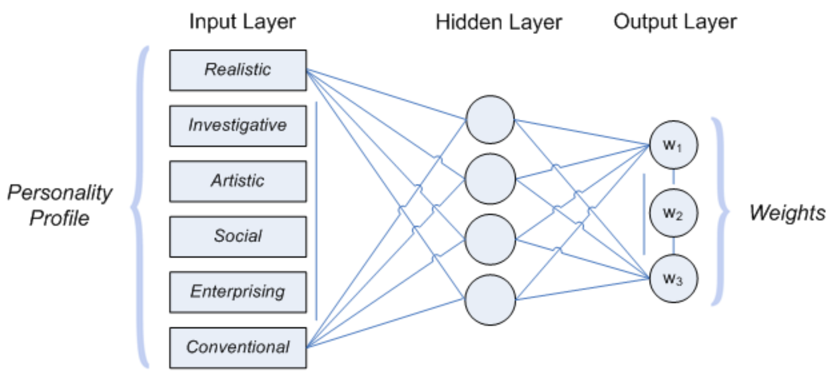

Fig. 1. Neural network that takes as input the user personality profile according to the RIASEC model, and returns as output the weights to be used in the combination of results from the different modules of the system.

4 Conclusion

In this article we have described a context-aware recommender system in the e-commerce domain capable of adapting the suggestion of products and services, not only to the user interests and preferences, but also to his personality. For this purpose, the system makes use of a neural network which takes as input the user personality profile according to the model RIASEC, and returns as output the value of the weights to be employed in the combination of the results coming from the different modules of the system. A prototype of the proposed model has been realized and is currently undergoing experimental validation. The first results we have obtained are encouraging and tend to confirm the validity and soundness of the advanced approach.

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References

1. Arnold, M.J., Reynolds, K.E.: Hedonic shopping motivations. Journal of Retailing 79(2), 77–95 (2003)
2. Biancalana, C., Flamini, A., Gasparetti, F., Micarelli, A., Millevolte, S., Sansonetti, G.: Enhancing traditional local search recommendations with context-awareness. In: Proc. of UMAP'11. pp. 335–340 (2011)
3. Caprara, G.V., Barbaranelli, C., Borgogni, L., Perugini, M.: The "big five questionnaire": A new questionnaire to assess the five factor model. Personality and Individual Differences 15(3), 281–288 (1993)
4. Holland, J.L.: Making vocational choices: A theory of vocational personalities and work environments, vol. 3. Psychological Assessment Resources (1997)
5. Hu, R., Pu, P.: A study on user perception of personality-based recommender systems. In: Proc. of UMAP'10. pp. 291–302 (2010)
6. McCrae, R.R., Costa, P.T.: Validation of the five-factor model of personality across instruments and observers. J. of Pers. and Soc. Psych. 52(1), 81–90 (1987)
7. Nunes, M.A.S., Hu, R.: Personality-based recommender systems: an overview. In: Proc. of the 6th ACM Conf. on Rec. Sys. pp. 5–6. RecSys '12, ACM, New York, NY, USA (2012)
8. Odic, A., Tkalcic, M., Tasic, J., Kosir, A.: Relevant context in a movie recommender system: Users' opinion vs. statistical detection. In: Proc. of the 4th Workshop on Context-Aware Recommender Systems (2011)
9. Rentfrow, P.J., Gosling, S.D.: The do re mi's of everyday life: the structure and personality correlates of music preferences. J. of Pers. and Soc. Psych. 84(6), 1236–1256 (Jun 2003)
10. Tkalcic, M., Kosir, A., Tasic, J.: Affective recommender systems: the role of emotions in recommender systems. In: Proc. of the 5th ACM Conf. on Rec. Sys. (2011)
11. To, P.L., Liao, C., Lin, T.H.: Shopping motivations on internet: A study based on utilitarian and hedonic value. Technovation 27(12), 774–787 (2007)
12. Tsao, W.c., Chang, H.r.: Exploring the impact of personality traits on online shopping behavior. Journal of Business Management 4(9), 1800–1812 (2010)