A personality based adaptive approach for information systems

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In every context where the objective is matching needs of the users with fitting answers, the high-level performance becomes a requirement able to allow systems being useful and effective. The personalization may affect different moments of computer–humans interaction routing the users to the best answers to their needs. The most part of this complex elaboration is strictly related with the needs themselves and the residual is independent from it. It is what we may face by getting personality traits of the users.

In this paper, we describe an approach that is able to get the personality of the users by inferring it from the social activities they do in order to drive them to the interactive processes they should prefer. This may happens in a wide set of situations, when they are deepened in a collaborative learning experience, in an information retrieval problem, in an e-commerce process or in a general searching activity.

We defined a complete model to realize an adaptive system that may interoperate with information systems and that is able to instantiate for all the users the processes and the interfaces able to give them the best feeling and to the system the highest possible performance.

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1. Introduction and motivations

Recent studies highlighted that to better satisfy goals of different users during a learning experience it is important to consider their personalities in order to find and deliver the best available material and to allow them being at ease (Chi, Chen, & Tsai, 2014). Other studies underlined that it is reductive to connect the employability only to the competence searching because it should analyse psycho-aptitude aspects in order to understand whether a user is recommended for a job, for a particular environment, for a work team, etc. (Crant, 2000). Moreover, as stated in Bologna (2013), during a game, a professional activity, an e-commerce tour or other kind of experiences that may be personalized, adapted, or simply chosen, keeping in mind these personal features should allow better understanding preferences and needs and easier satisfying them.

Thus, when an information system offers services to people, if it takes into account features of the users like the personality may improve its performance and the quality perceived by the users themselves. The main faced issue is the interaction between the user and a general-purpose system and which kind of personalization able to take into account personality aspects, we may adopt to allow individuals feeling better during this process.

In fact, in Nass and Reeves (1996) the authors claimed that people were inclined to treat media, usually computers in their studies, as if they were real people or real places, since the authors of Lewis (2013) assert that, when people interact with “something” having similar personality traits, their feeling is usually positive. This seems to be independent from the subject of the service itself and, thus, leads us to focus on the interaction with the user and on how we may improve it, allow users feeling better and, eventually, reach better results by collecting positive feedback.

The personality greatly influences our decision-making process; it can be a powerful tool in design (Aarron, 2011). When we develop software application by following new design approaches, we define “personas”.

Each “persona” identifies a stereotype of user having interests, expertise and needs and asking something to the system that we should translate in specific requirements. This description helps us to understand who the people are and gives some idea on which kind of personality they have, which motivation moves them to use the system and how to design interface and system in order to meet their features. The impact of these aspects has been treated in many context as in Zhang and de Pablos (2012), Zhang, de Pablos, and Xu (2014), Zhang, de Pablos, and Zhu (2012).

In Tera, Hyun, and Fisher (2009) authors establish that differences between users do influence the efficacy of visualization and web application interfaces and, so, they should be considered as a part of a maturing theory of visualization and complex interface design. In domain-specific interface, users often share certain
common problem-solving tendencies. By studying the group-specific inherent traits or behaviours of an expert cohorts, we may be better able to create visualizations that are discernibly more intuitively interactive in the environmental set for which they were designed.

Nowadays, systems usually have more than one interactive process with the user and many different interfaces. Often it is due to the needs to offer different accesses for different devices and connections. Well aware of this, we aimed to create a sort of plug-in for these information systems able to analyse the features of the users and create for them the best interactive environment by choosing processes and interfaces.

For the personality analysis, there are many theories and techniques. The first theories on personality tried to connect people to “personality stereotypes” having hard and schematic features. Carl Gustav Jung conceived one of these theories (Jung, 1971). Theories in the following years lead in the mid-twentieth century to more elaborated approaches and models. In the following subsections, we are going to summarize them.

The following Section 2 underlines other works related with the proposed approach that is described in Section 3. Section 4 shows the results of an early experimentation and give some evaluation elements. The last Section 5 depicts conclusions and possible future works.

1.1. The cattel theory

In his explorations on personality treats, the psychologist Raymond Cattell found that the variations of the human personality should be explained by mean of a model having sixteen variables (Cattell, 1956). His model is based on a statistical procedure, known as factorial analysis. His research results originated the theory on 16 personality factors (16PF): Abstractedness, Apprehension, Dominance, Emotional Stability, Liveliness, Openness to Change, Perfectionism, Privateness, Reasoning, Rule Consciousness, Self-Reliance, Sensitivity, Social Boldness, Tension, Vigilance, Warmth.

This theory includes a test able to identify the personality of a person with respect to the cited main traits. The evaluations adopt the International Personality Item Pool scale (Cattell, s.d.). For each factor, there are some features able to increase or decrease the evaluation.

The 16PF test is a set of questions that evaluate these main factors and some other wider ones, known as “global factors”. They are Introversion/Extraversion, Low/High Anxiety, Receptivity/Tough-Mindedness, Accommodation/Independence and Lack of Restraint/Self T Control.

This test, during the year, has been useful to evaluate personalities in both clinical and enterprise environments. Its limits are on the analysis of the evolutions and changes of the personalities and on the limited agreement on the number and nature of its factors.

1.2. Myers-Briggs type indicator

The Myers-Briggs Type Indicator (MBTI) (Myers, s.d.) is one of the most used test in the United State of America, especially for the selection of worker. This test is based on the theory of types of Jung (1971). The theory of Jung asserts that the different personalities have different way to perceive the world. There are four different channels and for each channel two different perception ways. These four dichotomies are Extraversion (E)–(I) Introversion, Sensing (S)–(N) Intuition, Thinking (T)–(F) Feeling, Judging (J)–(P) Perception.

The personality type is the result of the interaction of the preferences of a person represented by only one pole of each dichotomy. By combining these four indexes, we obtain sixteen different types of personality able to depict the profiles of the people. These profiles underline attitudes, mechanisms under decision processes, relations with the environment, but it is not an evaluation of the personalities in terms of positive/negative judgement. The Myers-Briggs test allows, thus, professional consulting in finding the best profile for a particular need or the appropriateness of a person in doing a job or getting some material for particular issues.

However, the statistical validity of this test has been criticized during the years (Gardner, 1996) because it leverages simplistic dichotomies and tenuous results.

1.3. The Big Five theory

Costa and McCrae formulated the Big Five theory (Costa & McCrae, 1992). It asserts that the personality of a person comes from a set of innate and unique features. It gets together the factorial approach of Eysenck (1979) and the Cattell’s theory.

McCrae and Costa identified five big dimensions of the personality:

- **Neuroticism**: tendency to experience emotional instability, anxiety, moodiness, irritability and sadness.
- **Extraversion**: excitability, sociability, talkativeness, assertiveness and high amounts of emotional expressiveness.
- **Openness**: imagination and insight, tending to have a broad range of interests.
- **Agreeableness**: trust, altruism, kindness, affection, and other prosocial behaviours.
- **Conscientiousness**: high levels of thoughtfulness, with good impulse control and goal-directed behaviours, tending to be organized and mindful of details.

These dimensions allow describing diversities of people and representing the point of convergence among measure models (i.e. 16PF). The Big Five theory differs the theory of types, thus the models inspired from it are different from the Myers-Briggs model. The main difference is on the way to evaluate some dimensions. For instance, the theory of traits evaluates introversion and extroversion as two extremities of the same concept, while the theory of types considers them as two attraction poles.

The measurement tool validated by Costa and McCrae is the NEO-PI (Neuroticism-Extraversion-Openness Personality Inventory Revised), a questionnaire structured by mean of the Likert Scale based on assertions semantically connected to behaviours to investigate and five possible alternatives of agreement: Strongly Agree, Agree, Undecided, Disagree, Strongly Disagree. The test, by using high-score and low-score features, identifies the intensity of each personality trait of a person.

In literature there are many different tools adopting the Big Five approach. The most famous is the “Big Five Questionnaire” (Caprara, Barbaraneli, & Borgogni, 1993). This theory is often used to evaluate personality in organizational contexts because the test is reliable. The main critic to the Big Five model received is on the heterogeneity of the resulting psychological profiles and on its results in some countries having different cultural influences as in Hungary (Szirmak & De Raad, 1994) (De Fruyt, McCrae, Szirmák, & Nagy, 2004).

1.4. The Holland theory

The Holland theory (Holland, 1973) gives its attention to the relations between the individual and the environment and underlines the importance of the analysis on the evolutionary history in the evaluation of the personality by taking into account aspects like education, childhood and socio-economical context.

Knowing the types of personality and the information on the environment allows forecasting the orientation in education,
professional training, employing, success, satisfaction, etc. The Holland theory has six personality types: Realistic, Investigative, Artistic, Social, Enterprising and Conventional.

The acronym used to identify these six categories is RIASEC. RIASEC allows classifying interests and professional profiles of an individual.

The graphical structure of the model uses a hexagon whose vertices are the RIASEC types. In the model, the physical distance corresponds to the conceptual connection.

The Holland theory treats also the work environments and allows describing them by using the same professional typologies. In fact, there is a strong relation between the individual and the environment. Thus, we may evaluate people and environments in the same way by using the same models. Individuals like the environments closer to their own personalities. When they are deepened in contexts distant from their personalities may change their own personalities or look for alternative contexts. Personalities and environments interact each other in a reciprocal process.

To better define the RIASEC types, Holland defined three indexes:

- **Congruence** of different types in the order of the hexagon.
- **Differentiation** of a trait on the other ones.
- **Consistency** of people, context and objectives.

Although the pioneering Holland’s work has an essentially empirical approach, it remains one of the most utilized approach to determine personalities, preferences and give professional suggestions to people.

### 2. Related works

In Ross and et al. (2009), the authors assert that it is possible to infer the personality of the people from the activities they virtually live in the social networks. In fact, the five labs solution is able to extract the personality of the users from the interaction they do in Facebook with their friends and contacts. The authors of Schwartz and et al. (2013) designed the approach implemented in this solution that analyses words, phrases and topic instances collected from the messages posted in social networks in order to observe individuals as they freely present themselves.

In Ozen and Kodaz (2012), authors examined the roles of hedonic and utilitarian values in online shopping by comparing cross culturally the Turkish and US consumers. They showed that the online shopping behaviours of Turkish and USA consumers differ according to their hedonic and utilitarian values. While Turkish consumers use online retailers to socialize with others, the USA people use online shopping for relaxation purposes. It does imply also that the interaction between the user and the system is different and this difference depends on the culture of the users and, thus, on their personality traits. By adopting an opposite approach, after having identified the personality of the people, we could identify which kind of interaction they probably prefer.

What has been studied for the online shopping, plausibly happens in other contexts where people have to interact with systems offering services through a user interface and it may needs different processes. In particular, this happens in collaborative learning situations where multiple processes may start and many users may be involved.

The problem is to lead back the personality traits of an individual to the right stereotype of motivations to take into account. A possible solution is what the authors described in Bologna et al. (2013), i.e. a system able to point out motivations from personality traits coming from a RIASEC profile or, similarly, by applying methodologies like those described in Schinka, Dye, and Curtiss (1997), from a Big-5 profile.

A possible alternative is a direct association between the user profile and the preferred interface/interactive process to follow. Frequently, this kind of approach, as in Liu, Osvalder, and Karlsson (2010), is adopted by linking the interaction to the general profile including competence, experience, preferences and, often, not explicitly including personality traits. However, the most part of these related works pays its attention to these aspects during the design of a software application instead of respect them at run time in order to apply some personalization or adaptation methodologies.

This seems to be a classification problem as in machine learning or statistics. The user profiles are the observations; the interactive processes are the categories. The users have preferences in terms of the interactive processes they would like to use. Thus, we may construct a training set by getting together observations and preferred category. A possible classifier should analyse the training set by using specific algorithms in order to be able to identify to which of the categories a new observation belong. A classifier like this, as described in Bishop (2006), may be realized by adopting approaches of pattern recognition as in Jain, Duin, and Mao (2000). The possible solution could be also an artificial neural network (a multi-layer perceptron). In the literature, there are many instances of these models for this kind of classification problems.

Since we do not have clear rules to apply and exact values to treat, the neural approach could be the most convenient.

In general, the personalization in human–system interaction aims to improve the features of the system itself and the performance referred to the users, especially when they have heterogeneous profiles, interests, backgrounds and specific needs. The personalization may affect different aspects of the interaction and it may address interface, content or process aspects by customizing them in order to better satisfy the user’s requirements.

It may happen at different levels and unquestionably lead customers to benefits since the increasing demand for Customer-Centric services started with the growing interest in personalization (Kingsstone, 2005).

In Goy, Ardissone, and Petrone (2007) the authors underlined the distinction between adaptable systems and adaptive ones. In adaptable systems, the user, who explicitly customizes the system to receive a personalized service, decides the adaptation. In adaptive systems, the system autonomously performs the adaptation without any direct user intervention. Although adaptability and adaptivity may co-exist within the same system, the first one is based on standard system configuration techniques largely applied in interactive and batch software applications. Often, from these kind of choices we may obtain different system configurations and, consequently, activate different kind of process and related interfaces. Moreover, the authors state that the personalization can be considered as an added value only if it represents an advantage by supporting long-term relationships between the user and the system, or by increasing the quality of the offer, by tailoring products and services to individual customer needs, or making easier the interoperability. However, as stated in Karat (2003), during the design and development of personalized systems, the real benefit of personalization is not known a priori, but it must be demonstrated within the context of any specific application.

### 3. Overall approach

The approach proposed in our work aims at the definition of a personality-based adaptive system that may interoperate with existing systems for learning or information and knowledge...
sharing and that is able to instantiate the best interactive process for the users.

When a system may offer services to the users by adopting different processes and related interfaces, the choice of the best interactive process is not clear a priori, but it may depend on a set of issues related to technical aspects (devices, connections) and personal aspects (time to spend, goals, feeling). When the goal is to offer services to the users in the best available way, the personalization may surely help and allow reaching high performance, usability and effectiveness.

We summarized in the following list the main steps we are trying to apply and we described them in the next sub-sections:

1. Getting the personality traits.
2. High-level personalization.
3. Low-level personalization.

3.1. Getting the personality traits

In the “Social Network Era”, the best available mean we have to understand which kind of preference, experience, profile and other features the users have, is to infer them by analysing the use the users do of the social networks themselves. This is what authors of Gianforme, Miranda, Orciuoli, and Paolozzi (2009) define “scru-tatable user modelling” as a way to describe the users by elaborating the posts they write, the friends they have, the knowledge they acquire, etc. We have chosen to extract the personality traits of the people by using the fivelabs solution that implements the approach described in Schwartz et al. (2013).

As showed in Fig. 1, the approach analyses all the posts the people wrote in a social network like Facebook² and tries to identify their features of neuroticism, openness, extraversion, agreeableness and conscientiousness.

Each user $u$ is identified by means of a vector $P_u$ having five different dimensions:

$$P_u = (p_1, p_2, p_3, p_4, p_5) \quad \text{where } p_i \in [0, 1]$$

where $p_1$ is the neuroticism, $p_2$ is the openness, $p_3$ is the extraversion, $p_4$ is the agreeableness and $p_5$ is the conscientiousness. Each $p_i$ is a percentage expressed from 0% to 100%.

3.2. High level personalization

When we have an application with more than one process of interaction with the users and more than one interface as well, we would demonstrate that a high-level (or macro) personalization could improve the feeling of the users during the interaction with the application itself and, consequently, the performance in the situation they are living.

As showed in Fig. 2, the processes and the related interfaces we took into account are very simple and have a large-scale deployment:

- Keyword-based discovery.
- Faceted browsing.
- Dialog-based interaction.

We may find these processes in a wide set of applications where the user has the need to look for something in a repository for different issues like learning, e-commerce and job finding.

The proposed High Level Personalization approach should get the vector $P_u$ for each user $u$ and suggest the best interaction to adopt. We should get the vectors of the personality traits of the users and associate to each of them the preferred interaction. We do not have any information about this kind of association, thus, we would investigate what are the preferences and create a classifier that, after a training and tuning phase, would be able to recommend to the users both process and interface they should prefer. As

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in Bologna et al. (2013), we have chosen to adopt an artificial neural network classifier because it allows us to use without defining any rules on these associations but by inferring them directly from the collected data.

This classifier has five input that are the components of the big-five vector identifying the personality profile of each user and three output that are related to the three different cited processes: **Keyword-based discovery**, **Faceted browsing**, **Dialog-based interaction**. By mean of the investigation, we may create a training set as defined in the following:

\[ TS = \left\{ (p_1, p_2, p_3, p_4, p_5, o_1, o_2, o_3) : p_i \in [0, 1], o_j \in \{0, 1\}, \sum_{j=1}^{3} o_j = 1 \right\} \]  

In each pattern of the training set, the first five components are the personality traits and the other three are the preferred interaction. If a user prefers the **Keyword-based discovery**, the first output will be 1 and the other two ones will be 0. Similarly, if the user prefers the **Faceted browsing**, the second output will be 1, the first one and the third one will be 0. Finally, if the user prefers the **Dialog-based interaction**, the third output will be 1, the first one and the second one will be 0.

By using the same neural network simulator used in Barile, Magna, Marsella, and Miranda (1999), we defined a neural structure having 5 input and 3 output according to the training set. We should train the neural network in order to forecast to the users the interaction process they should prefer.

### 3.3. Low-level personalization

The low-level (or micro) personalization phase has two main objectives:

- Improving the quality and the usefulness of the search results brought back to the user.
- Improving the quality of human–computer interaction process.

More specifically, the low-level personalization consists of:

- **Personalization and adaptation of the contents** proposed to the user (e.g. selection and filtering of the search results).
- **Personalization of the way** in which these contents are shown to the user (e.g. ranking of the results, personalization of the graphical interface, etc.).
- **Personalization of the interaction pattern**.

It is evident that the low-level personalization strongly depends on the particular human-interaction approach that is being considered: for instance, the way in which a keyword-based search interface is personalized differs from the case of a faceted browsing interface.

Our work focuses on the human–computer interaction for information retrieval. Even if much kind of information retrieval systems exist, it is possible to represent them with an abstract model that shows all the common capabilities among the different information retrieval approaches. This allows referring to these common capabilities to define the low-level personalization approaches that is possible to take into account for different kind of information retrieval systems.

Fig. 3 shows a model of human–computer interaction for the information retrieval.

A Mediator processes the user’s request and retrieves the information in a repository able to satisfy the user’s needs. The Mediator implements a three steps process:

- **User’s request interpretation**: the request of the user is interpreted by using the common shared knowledge stored in a Knowledge Base. Moreover, the user request is turned into a data format suitable for the processing in the following step. In the User’s Request Interpretation step, contextual information and user’s preferences are exploited in order to contextualize the request to the situation the user is involved in. When the mediator is unable to interpret correctly the request, it can...
involve the users in a clarification process in which the users are asked for clarifying their intention (e.g. by means of questions in a dialog-based interaction, or by means of facet selection in a faceted browsing, etc.)

- **Matchmaking**: by means of a matching algorithm, specific for the adopted information retrieval process, the mediator retrieves in a repository the information the user needs.
- **Ranking and selection**: the previously identified information is ranked and filtered with respect to contextual information, user’s preferences, explicit filters set up by the user, etc.

Let us consider three different information retrieval approaches, represented as instantiation of the proposed model.

**Fig. 4a** represents a Mediator for a faceted browsing approach to information retrieval. Faceted browsing implements an exploratory search paradigm. In the exploratory search (White & Roth, 2009), the user information need is generally open-ended. Open-endedness relates to the uncertainty over the information available or incomplete information on the nature of the search task. The goal behind an exploratory search goes beyond simple information lookup: it regards helping people in making a decision or deepen their understanding, with regard to a topic of interest. As a matter of fact, the exploratory search activities are always coupled with a vague and fuzzy information need.

In the faceted browsing, the interaction between user and system is limited to the selection of facet values by the user. Thanks to these facets (contained in a facets taxonomy stored in the Knowledge Base), the users can focus their vague research so to filter search results. As a result, the User’s Interaction Interpretation in the Faceted Browsing Mediator consist of acquiring the facets that have been selected by the user and give them to the Matchmaking module. This module uses the selected facets for filtering search results and for identify which new facets can be proposed to the user for further filtering the research. The results and the facets are ranked by the Ranking module before to forward them back to the user.

**Fig. 4b** depicts the Mediator for Keyword-based search. In this approach, users have a very specific information need and are able to fully express it by means of query searching. Generally, discrete and well-structured objects are returned as a result. This kind of searching is also defined as goal-oriented search, in contrast with the exploratory search of the previous approach. According to Zhang (2008), in exploratory search, users issue queries for identifying what the system has to offer. Whereas, when using
goal-oriented search mechanisms, they ask to the system what they want.

Keyword-based searching relies on an automated keyword matching strategy, mapping terms, describing a query, describing documents contained in a repository. Searching by means of a keyword-based system generally requires shorter time, and thus fewer interactions, than the exploratory approach.

The user's interaction merely consists of a query made of several keywords. The User's Interaction Module has to process these keywords (by means of Natural Language Processing (NLP) techniques, like tokenization, stemming and stop word removal). Moreover, it disambiguates the keywords with ambiguous meaning, by exploiting the knowledge contained in the Knowledge Base. Lastly, some approaches use query expansion to improve the effectiveness of the search, by including in the query related keywords, user's preferences, etc. The result of this module allows the Matchmaking module formulating a query that will be executed on the repository to retrieve the desired information.

The results of the matchmaking, represented as semi-structured information, are ranked by the Ranking module with respect to the relevance of the information for the user's query, to the contextual information and to the user's preferences.

Lastly, Fig. 4c shows the dialog-based approach for information retrieval. In this approach, user and system communicates by means of dialog. A dialog an exchange of speech acts between two speech partners, in turn-taking sequence, aimed at a collective goal. In particular, the dialog is used in order to clarify the users' intention and to better understand their goal. This kind of approach tries to combine the advantages of both exploratory and goal-oriented search: the interaction generally starts by an explicit request of the user (goal-oriented). Next, the dialog evolves for clarifying user's needs and for refining search results (as in an exploratory search).

The approach foresees the interpretation of user's sentences by means of Natural Language Processing techniques and Conceptual Knowledge (to give a meaning to user's sentences). In cases in which user's sentence is not understood by the system, the latter uses to dialogue to clarify the user's intention. When the user's request is clearly interpreted, the Mediator retrieves the desired information in the repository (as in the keyword-based approach). Lastly, the list of results are ranked and a system response (in the form of a dialog sentence) is forwarded to the user.

4. Early experimentation and evaluation

Starting from a set of about 600 contacts, we extracted their personality traits by using the fivelabs solution.
To all contacts, we described different interactive processes, we showed the related interfaces and we asked them to select which was the process they preferred.

By means of a poll on Facebook¹, as showed in the following Fig. 5, we asked, for a specific e-commerce issue (e.g. looking for a restaurant, booking a room in a hotel), which kind of interaction the users preferred. In few weeks, about a quarter of them (126 users) gave us an answer underlining what was their choice.

By using vectors $P_u$ for all users $u$ that participated to the poll and the answers they gave, we constructed a training set to use to train the classifier. The following Fig. 6 shows a chunk of this set with no details on names of the users for privacy reasons.

From this set, we constructed the training set as showed in the following Fig. 7.

We defined a neural structure having 5 input and 3 output according to the training set and two hidden layers each of them having 20 neurons.

As suggested in Bishop (2006), we split TS in two parts. One for the training and one for the testing. How many patterns to use in each set is a still open research problem because in the training set we should get a significant set of patterns able to describe the phenomenon we are studying and the testing set should be wide enough to be confident that the classifier has been trained well. Thus, the best compromise to use is 66.6% for the training set and 33.3% for the testing set. By using these percentages, we created the first set of 80 patterns for the training and the second set of 46 patterns for the testing. It means that the algorithm trains the network on only the first part and evaluate its effectiveness in classifying patterns by getting its outputs on the other patterns coming from the second part (the testing set).

After about 20,000 iterations, as showed in Fig. 8, the algorithm trained the neural network and showed less than 2% as maximum error on the used patterns and less than 8% on the patterns of the testing set.

Thus, we may assert that the classifier is ready to use. Now, we may adopt it to support the high-level personalization: for the new users, we may extract the personality vectors and, by using the trained neural network, we are able to forecast the interaction processes they should prefer.

5. Conclusions and future works

We defined a new adaptive approach that is able to suggest the best interactive process to the users that are engaged in using applications whose general main issue is to provide information. It may happen into a wide set of contexts like collaborative learning, knowledge management and information retrieval. Of course, when an application offers different possible available interaction paths, the way to provide services and results is important for the user’s feeling and, often, for the performance of the application itself.

The proposed approach includes only two different layers of personalization starting from the extraction of the personality traits of the users from the social networks and tries to suggest the interaction processes by means of an artificial neural network. We did a very small experiment and we are not sure on how many contexts, applications and issues we may face, but the results we gain are very encouraging in going on with this research activity.

To evaluate the effectiveness of the interaction processes suggested by the neural prototype for the users, we should do other experiments by engaging a wide set of users that did not give any answer to the poll. We should divide them in four groups: an experiment group and three different control groups. Only to the first group we should allow our prototype suggesting the interaction way. To the other three groups we should submit the three different interaction processes. We should not collect their feedback about what the perceived, but we should just track if they complete the purchase or not. From all the tracked data, then, we should point out which kind of interaction gains the best performance. Of course, we will expecting that it will come from the users that receive personalized interactive process and related interfaces.

We are interesting in collecting feedback from any kind of activities that engaged users and drive them to the information they are looking for. By means of the evaluation of the results, we may indirectly evaluate whether our proposed approach may improve performance of systems and, in particular, for collaborative and learning experiences, if it may improve interactions and learning outcomes.

References


Cattell (s.d.) Personality testing. <http://personality-testing.info/tests/16PF.php>


Ozen, H., & Kodaz, N. (2012). Utilitarian or hedonic? A cross cultural study in online shopping. Organizations and markets in emerging economies (Vol. 3 (no. 2(6))).


