

## PERSONALITYML: A MARKUP LANGUAGE TO STANDARDIZE THE USER PERSONALITY IN RECOMMENDER SYSTEMS

Maria Augusta Silveira Netto Nunes; Jonas Santos Bezerra; Adicinéia Aparecida de Oliveira

Universidade Federal de Sergipe – UFS – São Cristóvão/SE – Brasil  
[gutanunes@gmail.com](mailto:gutanunes@gmail.com), [jonassantosbezerra@gmail.com](mailto:jonassantosbezerra@gmail.com), [adicineia@gmail.com](mailto:adicineia@gmail.com)

### Abstract

*In recent years the study of how human psychological aspects may improve the decision-making process in computers has become a new trend. This subject has attracted the attention from both academy and industry in areas such as human-computer interaction, computer in education, recommender systems and social matching systems, among others. However, one of the biggest problems faced by them is how effectively to use, model and implement those psychological aspects in computers. This paper comes to fill partly this gap by proposing a markup language to standardize the representation of personality. The PersonalityML proposes a set of recommender inputs to be used as starting data to classical cold-start problem in recommender systems, as well as, in personality-based recommender systems and others personality-based web applications.*

**Key-words:** User modeling, Personalization, Personality-based recommender systems, PersonalityML, Recommender inputs

### 1. Introduction

In the e-commerce environment, the industry is constantly searching for innovative technologies that enable it to treat properly the overload of information, products and services available on the web business. Their main concern is about how to reach personalized and customized offers in order to predict consumer behaviors and then satisfy their expectancy.

The most used technology for treating overload and personalizing information, products and services in e-commerce is recognized as Recommender Systems (Resnick and Varian, 1997). Researchers such as Burke (2002) proposed at least five techniques for recommendation. Those

techniques come to treat the overload problem considering the type of information to be matched towards to personalization. Burke defined them yet as five major techniques: content-based, collaborative filtering, demographic, knowledge-based and utility-based. However, those techniques could not manage adequately the cold-start problem (Schein et al, 2002) caused mainly by the sparse data and/or new user. This problem was partially solved by the hybrid technique, according to both Burke (2002) and Adomavicius and Tuzhilin (2005). A hybrid technique incorporates, at least, two of the already described techniques; usually the collaborative filtering and the content-based techniques are put together.

Even by incorporation of at least two techniques many times the cold-start problem persist yet in recommender systems. Let's consider the computer in its decision-making process in an overload situation where human efforts could be unable to treat, why computers consider only the information conventionally processed by computer in its decision-making? We mean, take a real situated context such as buying. In that scenario, how the store's vendor could partially perceive and extract the consumer behavior and subtle information during his interaction with a client? The answer is: the vendor may extract clients information's during his interaction, like (i) what type of clothes the client is using; (ii) what type of shoes she is using; (iii) is she using watch?; has she a bag?; (iv) does she use a make up?; (v) is she wearing jewelry?; (vi) how about her haircut?... And how about another subtle information, like: (i) her speech intonation; (ii) her facial expression; (iii) her gestures; (iv) her body language.... All that information, in a conventional shopping situation, is extracted by the physical/real vendor from a client during their interaction. From that observed data the vendor predicts what type of product the consumer could be interested in. This type of information has already taken into account by marketing strategies in order to predict costumers' behavior (Sandhusen, 2008) (Solomon, 2010). However why that subtle information is not used by computers in its decision-making process? Is this type of information even collected from user during his interaction with computers? Have they a standard representation in computers?

Subtle information is extremely important for human decision making process, as proved in studies from (Damasio, 1994), (Simon, 1983), (Picard, 1997), (Trappl et al, 2003) and they have demonstrated how important psychological aspects of people such as personality traits and emotions are during the human decision-making process. Even marketing scientists have already described how mandatory this data could be in order to discover the most assertive prediction.

Many subtle information are freely available on web through social networks, blogs, sms, for instance, the question is how to extract them without being too intrusive, and, more importantly, could those subtle information be standardized? Then, how to standardize those data in order to

enable to any system perceive and use effectively this information as recommender inputs for web systems.

Next, in this paper, we present the growing up field of personality-based recommender systems, followed, in section 3 by some definitions of personality, describing the main used approach implemented in computers. Followed by some developed computer-based tools that enable computers to extract the personality considering the trait approach. In section 4, we present some patterns used as computational models to represent psychological aspects like emotions. In section 5 we describe how to represent that data to be used in web systems. In section 6 we present our proposal of standardization, the PersonalityML with some examples. And finally, in section 7 we present some conclusions followed by paper references.

## **2. Towards to personality-based recommender systems**

Since the 70s Affective Computing scientists have been trying to model human psychological aspects (mainly emotions) in order to implement what they believe to be lifelike agents, as seen in the works like, (Rousseau and Hayes-Roth, 1998)(Ortony et al, 1988)(Lisetti, 2002)(Picard, 1997), amongst others. As people have psychologically answered to interactive computers as if they were humans, Affective Computing scientists have tried to model lifelike believable characters with Personality, goals and human-like emotions because it contributes to coherence, consistency and predictability in computer emotional reaction and responses (Ortony et al, 1988). The Personality of an agent can produce a performance that is motivated, believable and “theatrically” interesting for users (Rousseau and Hayes-Roth, 1998).

However, in order to promote a different use of this type of subtle information, the recommenders’ scientists tried firstly understanding what Affective Computing scientists have effectively done in order to model lifelike believable characters. This approach is quite important to our work because the work already done by Affective Computing scientist may drive us with some fundamental cues and insights about how psychological aspects might be used and how much computers’ decision-making could be influenced by it. We have no special interest in deliberately produce emotions in users like lifelike agents do. However, we just hope to make computer understand and extract users’ psychological aspects to better personalize and recommend web information, products or services to them.

The use of subtle psychological information such as Personality Traits in recommender system started to be treated by Nunes (2007)(2008)(2009). We noticed that the work from Hu since 2009 (Hu and Pu, 2009) has also been developed towards to incorporation of personality in

recommender system (Hu and Pu, 2010) aiming to address an alternative to treat the cold-start problem (Hu and Pu, 2011).

In (2009) Hu and Pu compares a personality quiz-based recommender system with a classical rating system both on the music context. They discovered that users felt more positive results in the personality quiz-based than in classical rating recommendation. According to them, the user perceived less effort and task time in the personality quiz-based. They also affirms that user also demonstrated the stronger intention of reuse this type of quiz, and demonstrated good surprise with this approach because of the personality-based method may reveal his hidden preferences improving the recommendation as a consequence. In (Hu and Pu, 2009a), they complements the results of (Hu and Pu, 2009) by using TAM (Technology Acceptance Model).

In (2010) Hu and Pu compile the results of (2009)(2009a). They investigate the use of quiz-based personality also to create the psychological profile of the user's friends. Enabling for the music recommender system the generation of the recommendation both for the user and his friends. They notice that personality-based recommender system is more welcome for users who are not specialist in music and usually do not know what kind of music they prefer.

In (Hu, 2010) Hu gives an overview of her work focusing on the partial results extracted from her recent work. She declares, like in Nunes (2008)(2009), that personality influences human decision-making process and interests, and, she also affirms that little research has been done in this context. Her aim, as well as the paper's authors, is to contribute towards this field. Then in this paper she proposed a personality-based recommender system, which is effectively tested in (Hu and Pu, 2011). In (2011) Hu and Pu incorporate the personality information in the collaborative filtering approach aiming to reduce the cold-start problem using at least three methods. They got statistical interesting results from them proving that personality could effectively address the cold-star problem.

Lampropoulos et al (2011) propose also to solve the cold-start problem by using both content-based (music genre classification) and collaborative filtering technique (of personality diagnosis).

Tkalcic et al (Tkalcic et al, 2010) uses affective parameters, including personality traits, in order to recommend images in a content-based recommender system.

In 2011, many other recommender systems using personality appear, mainly in music recommendation domain such as proposed by (Lampropoulos et al, 2011)(Park and Moon, 2011)(Zhou et al, 2011). Other contexts different from music recommender also appear, they are: privacy management preferences influenced by people personality (Page and Kobsa, 2011), the associations between social media use and personality traits (Zhong et al, 2011), the association

between personality and the user language expressed in blogs (Iacobelli et al, 2011)(Minamikawa and Yokoyama, 2011) and in online tourism domain (Roshchina et al, 2011), the association between personality and popularity of users in the Facebook (Quercia et al, 2012), how adaptive user interfaces for mobile can be considering the user personality (Oliveira et al, 2011), among others.

### **3. How about personality**

Personality does not have a common definition. The Latin origin of the word personality, “Persona”, refers to a mask used by an actor in a play to show his appearance to the public (Schultz, 1990). Funder (2001) says that “Personality is also related to human thinking patterns, emotions and behaviors together with psychological mechanisms behind those patterns”.

We know that personality is more than just superficial physical appearance. Personality is relatively stable and predictable. However, it is not rigid and unchanging, it is normally kept stable over a 45-year period which begins in young adulthood. According to psychologists definitions of personality could be better defined based on the theory/approach of personality that it belongs to. Theories of Personality were created to facilitate the individual understanding of oneself and others. There are more than 18 theories of personality described by researchers. Each one describes alternative ways to present and differentiate human personality. According to Schultz (1990) they can be grouped in 9 categories: psychoanalytic, neopsychanalytic, trait, life-span, humanistic, cognitive, behavioral, social-learning and limited-domain. Alternatively, Funder (2001) also propose other categorization approaches, like: trait approach, biological approach, psychoanalytic approach, phenomenological-humanistic approach, behavioral approach and cognitive approach.

Each theory/approach of personality focuses on how personality is used and defined by psychologists and how each approach differ from one another in terms of conceptions and measures. Funder (2001) argues that people's unconscious minds are largely responsible for important differences in their styles of behavior. On trait approach, for instance, psychologists focus their efforts on the ways people differ psychologically from one another and how these differences might be conceptualized or measured (personality traits). Psychologists using the biological approach, point to inherited predispositions and physiological processes to explain individual differences in personality. In the phenomenological/humanistic approach, personal responsibility and feelings of self-acceptance are identified as key causes of differences in personality. Psychologists who adhere to the cognitive approach conduct experiments on how the basic cognitive processes of perception, memory, and thought affect behavior and personality. The

behaviorist/learning approach focuses on behavior and ways in which it can be affected by rewards and punishments.

Then, in this paper we propose to create a computer standardization of personality to be used as recommender inputs in the computer's decision-making process. We believe the standardization will facilitate how academy and industry may model and implement personality patterns in recommender systems and other web systems.

### **3.1 The trait approach**

According to Mairesse et al (2007) and Nunes (2008)(2009), the most common approach used by Affective Computing scientists to implement personality in computers is the trait approach. The main explanation for that is because the trait approach describes the psychological differences amongst individuals and it is easier than others approaches to stereotype, codify and implement in computers.

Personality traits were first studied and defined by Gordon W. Allport (1921). Allport studied personality based on healthy people as opposed to his colleagues who studied abnormal and pathological personalities (Schultz, 1990). He created 17.953 traits to describe the personality of an individual (Funder, 2001). Allport believes that every human is unique having common and individual traits. Therefore the intensity of those traits will be forcedly different. That means, for instance, "Mary and Jane may be both aggressive people, although the range of aggressiveness of each one will be different". That difference comes from their individual history and never-repeated external/environmental received influences. Thus, even if Mary and Jane have the same trait (aggressiveness) the intensity will not be the same.

Allport defines common traits those ones shared amongst many people within a culture, measurable on a scale. On the other hand, individual traits are traits that refer just to personal dispositions, unique in an individual. 17.953 traits defined by Allport include common traits as well as individual traits and says that "every man is: like all other men, like some other men and like no other men". As most individual differences are meaningless in people's daily interactions, in order to limit the definitions of traits in an exponential way, otherwise growing exponentially thus becoming intractable. Then researchers assume that the trait approach is based on the idea that all men are "like some other men" (Funder, 2001).

In this regard, Cattell proposes a subset of Allport traits. He proposes 4.500 traits items against the 17.953 created by Allport. Those 4.500 were correlated to 171 scales after some empirical analysis (Goldberg, 1990). After, Cattell reduced an extra 99% of those items transforming them into 35 bipolar sets of related items, which were factor analyzed. As a consequence, he

identified 16 personality factors. They were analyzed by orthogonal rotational methods, which proved that only five factors were replicable (Goldberg, 1990), as a result, the “Big Five” Model was created.

The formal beginning of the Big Five (John and Srivastava, 1999)/FFM (Five Factor Model) (Mcrae and John, 1992) was created by Fiske, replicated by Norman and derived from Cattell's natural language traits. They were usually labeled as (i) Extraversion, (ii) Agreeableness, (iii) Conscientiousness, (iv) Neuroticism and (v) Openness to Experience (Mcrae and John, 1992).

Essentially, to simplify and organize the traits, researchers created the Big Five model. On the other hand, researchers asked one another if only five traits were sufficiently accurate to measure personality differences. According to John and Srivastava (1999): “The Big Five structure does not imply that personality differences can be reduced to only five traits. Yet, these five dimensions represent personality at the broadest level of abstraction, and each dimension summarizes a large number of distinct, more specific personality characteristics called facets”.

Our study focuses on the definition of factor and facets because it is simpler and it is much more used by Affective Computing scientists than others approaches. Facets are used by psychologists in order to enrich Big Five dimensions with more fine-grained characteristics.

### **3.2 How to extract personality traits from user?**

In order to extract human traits, as Big Five factors and their respective facets, Affective Computing scientists started to use computer-based tools. Those tools could be questionnaire-based, stories-based, text-based, keyboard-based, kinect-based among others.

#### **3.2.1 Questionnaires**

Questionnaires are the most traditional way to extract user personality used nowadays. Traits questionnaires could be directly applied by psychologists, or may be freely available on the web. They might have either a large or a small amount of questions. The number of questions in the questionnaire is directly related to the granularity of the desired extracted traits from each person's personality.

A personality test is a computer narrative that generally reveals an established set of traits of an individual that differentiates one from another human being. Johnson's (Johnson, 2000) defines it as “a report based on empirical research that can tell a test-taker how someone's personality is likely to influence job performance, health, relationships and other significant life events, being useful to provide insights and to make predictions about individuals”.

Researchers propose a wide range of test to assess human personality traits (many of them are available in computer-based format). For instance 16PF (Cattell's 16 personality factors

questionnaire) and 6FPQ (six factor personality) are based on other constructions, different from the Big Five. Therefore, as described before we are particularly interested in personality tests based on 5 constructions (Big Five).

After analyzing a list of Inventories (described in (Nunes, 2009)) we hypothesized that the number of items influence the precision of the traits measured. The bigger the number of items, the finer grouped and more accurate the extracted traits will be. She described that NEO-PI-R is different from most other inventories. That is because it assesses 5 factors of Big Five including also 6 more facets for each dimension (30 facets in total) using then a fine-grained description of people's personality traits and, consequently, a bigger precision in those representations of traits.

Johnson (2000)(2005) defined the NEO-PI-R (Costa and McCrae, 1992) as one of the most robust, used and well-validated commercial inventory in the world. It has been used in over a thousand published studies where it demonstrated longitudinal stability, predictive utility, and consensual validation. The NEO-PI-R is a commercial inventory and, consequently, a proprietary instrument, (as most of broad-bandwidth personality inventories) its items are copyrighted and cannot be used freely by other scientists.

Alternatively, Goldberg has proposed in collaboration with some researchers the creation of a public domain scale called IPIP - The International Personality Item Pool (Goldberg, 1999). According to Johnson (2000) the IPIP Consortium created a set of 1252 items in the IPIP. Goldberg's research team has been able to identify, empirically, sets of IPIP items that measure the same constructions as commercial inventories. Scales formed from these items' set possesses psychometric properties that match or exceed those of the original commercial scales. In order to find a taxonomic framework to organize the nearly countless variety of individual differences that might be measured, IPIP also uses a Big Five factor structure as NEO-PI-R does.

The NEO-IPIP Inventory (Johnson, 2000)(Johnson, 2005) appeared when Johnson chose from the various personality inventories at Goldberg's IPIP website with his 300 items proxy for the revised NEO Personality Inventory (NEO-PI-R) (Costa and McCrae, 1992). Johnson decided to create an IPIP-NEO because it is a free-of-charge version of NEO-PI-R which is, as previously described, one of the most robust, known and well-validated commercial inventories in the world (Johnson, 2000) and also because it is based on Five-factor or Big Five dimensions. NEO-IPIP Inventory was used and well-validated by Johnson (2000)(Johnson, 2005). From August 1999 to May 2001, 175000 people answered the online NEO-IPIP questionnaire. Then, 21588 answered questionnaires were selected as a valid protocol.

As the time to answer a reputed fine-grained Personality Inventory (like NEO-IPIP for instance) may be limited, shorter instruments should also be provided. Even if inventories that

incorporate only five dimensions can not provide the specific variance associated with each of the lower-level facets (Goldberg, 1999) and long instruments tend to have better psychometric properties than short ones (Gosling, 2003), in real circumstances researchers have no choice other than using an extremely brief instrument (or they use no instrument at all).

In order to solve this problem, Gosling (2003) proposes a very brief Personality Inventory called TIPI test. TIPI (Ten-Item Personality Inventory) consists of 10 items based on the Big Five factors. TIPI is also an instrument of public domain. Gosling stresses that “a very brief measure should be used if Personality is not the primary topic of the research interest because a very brief measure can decrease psychometric associated proprieties”. Gosling found a strong correlation between the TIPI and NEO-PI-R dimension scales.

In Nunes (2009) we have been using the NEO-IPIP Inventory and TIPI test in order to conceive, model, formalize and implement a Psychological Profile to be used in our personality-based recommender System. In addition, her team has been developing other two updated versions of the questionnaire’s tool (Nunes et al, 2010), the last one is being developed to be used on mobile devices.

Both Dunn et al (2009) and Hu and Pu (Hu and Pu, 2009) (HU and Pu, 2010) agree that users fell comfortable and satisfied by having their personality explicitly extracted from a personality tool. Dunn et al, yet describe that the user demonstrated more satisfaction in answer a NEO interface (similar than NEO-PI-R and NEO-IPIP presented before) than other interface tested by them. However, Dennis at al (2012) found evidences that a stories-based “questionnaire” could be also more pleasant and effective than traditional questionnaires. The stories used by them are created taking into consideration the NEO–IPIP-20-item scales combining phrases into sentence forming a short story, presented inside a stories’ scenario. The results of their research are promising and interesting, however they did not found correlation in all five factors of Big Five.

Although researches about how to extract personality without using questionnaires are yet based on the assumption that human beings left personalities cues in all their daily life activities (Gosling, 2003). Affective Computing scientists are studying other methods than questionnaires towards to the extraction of user’s personality. Those methods include, for instance: speech intonation and conversation analyses (Gosling, 2006), text mining (Mairesse et al, 2007), typing and mouse use patterns (Filho and Freire, 2006) and (Porto and Costa, 2011), among others.

### 3.2.2 Keyboard-based

Unlike the questionnaire, the use of typing patterns to extract personality features is a less stressful and intrusive to the user. We mean, questionnaires are too much time-consuming and

require cognitive efforts from the user, while typing analysis is an automatic method and “invisible” for the user.

According to Filho and Freire (2006) the main way to obtain typing features is (i) by the time of latency between pressing two keystrokes and (ii) by the time pressing and holding one single keystroke. They show evidences that typing features are personal and can be used as components to improve biometrical systems. Then, Khan et al (2008) conducted experiments in order to measure personality via typing and mouse use patterns. They found promising results in recognition of some traits and facets by using this approach. In 2011, Porto and Costa (2011) proposed a system able to extract the user personality considering the user typing pattern. The methodology used by them was to map the user’s typing pattern extracted from a conventional keyboard (Filho and Freire, 2006) matched into the user personality traits extracted by the Personality Inventory (Nunes et al, 2010).

### 3.2.3 Text -based

Mairesse et al (2007) was the pioneer in automatic recognition of personality traits by using linguistic features. Based on text samples and conversation transcriptions collected from people he constructed a statistical model to evaluate personality. His model use both syntactic and semantics language information to recognize the Big five factors.

The author analyzed several ranking models and classifiers and made a list of advantages and disadvantages to personality recognition of each one of the Big Five factors. In his work, the ranking models were more accurate than the classifiers.

There are other new brand technologies to extract personality from user, such as kinect-based in emotion (Mahmoud et al, 2011). However the researches are just in the beginning and the results are not conclusive yet.

Thus, after extracting the user personality how to formalize it in a standard pattern? This paper fills this gap by proposing a Mark-up Language to represent personality data, called PersonalityML.

## **4. Developed patterns for human psychological aspects in computers**

As personality implies emotions, many Affective Computing scientists have been incorporating personality traits in their modelling of lifelike emotional believable agents, as described previously. In order to better use and apply user’s psychological aspects in other contexts such as recommender systems, we should firstly have a better understanding what Affective Computing scientists have been doing towards extracting personality aspects from human and then,

model in virtual embodied emotional agents. Based on this study, we took cues on how they have modelled agents' psychological aspects (real/virtual), even if our main interest is to use it to model human beings instead of virtual agents.

As we saw in the sections below, Affective Computing scientists are neither proposing newer personality nor emotional theories, they have only used the available ones in order to drive their models. However, at least considering the personality issues we did not find any pattern or standardization in their representations. By recovering human personality and storing in a standard model, we enable computers to manage the recommender inputs for its own decision-making process, which is essential during the recommendation process.

However, as we said before, many Affective Computing scientists focused mainly on the identification and model user's emotions (Rousseau and Hayes-Roth, 1998)(Ortony et al, 1988)(Lisetti, 2002)(Picard, 1997). Some examples of Computational Model of emotions are:

- AKR (Affective Knowledge Representation) is a taxonomy for Emotion, Moods and Personality, based on 16 different dimensions called emotional components (Lisetti, 2002);
- MOUE (Model of User Emotions) is a user model based on AKR. It store information about users' emotion; it calculates the most experienced ones; it classifies similar emotions and provides user feedback about his emotional state (Bianchi-Berthouze and Lisetti, 2002);
- User Mood is a XMPP (eXtensible Messaging and Presence Protocol) extension, created in XML and used to transport and store information about users' mood (Saint and Meijer, 2008);
- EmotionML (Emotion Markup Language) is the first W3C effort in order to standardize the representation of Emotion in computers (W3C, 2010).

Yet, even if emotions are more studied than personality, personality is more stable and lifelong and also it influences emotions directly. Unfortunately, there are little works using personality model, especially if compared with the use of emotions. Nevertheless, there are some starting relevant contributions in the field, such as:

- GUMO (General User Model Ontology) is an ontology designed to be used in ubiquitous computing in order to store and share user data through different kinds of technologies. GUMO was the first User Profile created to represent psychological information of (Heckmann 2005);
- UPP (User Psychological Profile) is a user model used to model users' personality according to the Big-Fivel Model based on the trait approach. It is used in a Personality Inventory and in a Personality-based Recommender System (Nunes 2008, 2009);

- Personality Recognizer is an application that automatically recognizes a user's personality using both linguistic and conversational cues (Mairesse et al, 2007).

## **5. Personality Markup Language**

### **5.1 How to represent data for web use**

Nowadays, the use of the web as an environment for sharing and produce the information's is a world reality in almost all levels of our society like economic, commercial, social, political and cultural.

According to Abiteboul et al (2000) a few years ago the e-data production was little and restricted, but nowadays most of people, companies and institutions share documents through web. However this type of data is usually computer generated using a database technology. How about to the development of a standard language for the electronic representation of data aiming to improve its publication and allowing both human and machine to understand "what is being said"? Such standardization is called eXtensible Markup Language, the XML.

XML is a standard of the World Wide Web Consortium. Used as a text-based format for representing structured information such as documents, data, configuration, transactions and so on. As well as one of the most widely-used formats for sharing information among programs, people and computers (W3C,-XML 2010).

Due to its extensibility (new tags and attributes can be defined by the programmer), complex structures (the powerful structure representation) and validation (XML documents may contain a grammar description), XML is also considered a meta-language. So it can be used as a start point to build more specific data representation. Some examples are :

- XBRL (eXtensible Business Reporting Language): used as a standard to publish financial reports, distribute financial information for banks, to fulfill the Security and Exchange Comission rules and insert financial information in websites (Riccio et al, 2005).
- UserML (User Markup Language): "a platform for the communication about partial user models in a ubiquitous computing environment, where all different kinds of systems work together to satisfy the user's needs" [18].
- ODF (OpenDocument Format for Office Aplications): is a XML-based file format for word processing, spreadsheets, presentations and charts. ODF is an international standard supported by multiple applications, and it can be implemented in any type of software (Oasis, 2012).

- EmotionML (Emotion Markup Language): a W3C standard markup language to computational representation of emotions (W3C, 2010).

All these languages and formats, developed in XML, allow us to take advantage of the entire XML infrastructure and technology. Taking also into consideration that XML was designed to represent and transport data through the web and has already a very disseminated technology; actually it is the most common tool for data transmissions between all types of applications.

## **5.2. Standardization of personality: PersonalityML**

The Personality mark-up language (PersonalityML) has the aim of standardize and help to disseminate and share the use of users' personality information across applications that take human psychological aspects into account in the computer decision making process.

As was demonstrated in the last section, XML can be used to build new mark-up languages for specific purposes without concerning about data sharing, data transport, data conversion or platform changes.

Thus, the main challenge when defining a markup language to standardize the representation of personality is to embrace the variety of psychological theories to explain personality once it does not have a common definition.

In order to create the PersonalityML we proposed an initial grammar, enabling the standardization of how represent the personality theories. We created a flexible initial grammar enabling the Affective Computing scientists add and extend whatever element they want in already defined theory.

The main attributes of PersonalityML are:

<personality>; <approach>; <model>; <theory>; <inventory>; <factors>; <facets>; <generic>. Described as follow:

- The <personality>: This element describes a single personality annotation and can be complemented by its sons. Attributes as <name> and <score> can also be used to improve the information about the PersonalityML tags.

- The <approach>: Approaches refer to “what” variables are used to understand personality. As an example, the trait approach explains personality in the ways people differ from one to another, the biological approach does it by using biological mechanisms, and so on. The set of approaches are listed before in section 3, or you may find a complete and more detailed list at (Funder, 2001).

- The <model>: Once the same emphasis or approach can use different models to represent personality, like the FFM and the Big Five based on the trait approach, this element is used to assign what model is being used at the moment.
- The <theory>: The element theory is used when the programmer needs to specify the theory adopted and the author – by using its attributes – that theory belongs to.
- The <inventory>: This element describes the method used to extract personality, we mean if it was a questionnaire, text automatic recognition, stories, and others, as well as what questionnaire, what text recognition framework, etc.
- The <factors>: Used to specify a set of factors or components that will be used to measure the personality. Such as, what factors are used when using the trait approach.
- The <facets>: Some theories or models require further detailed explanation than that given by the use of a set of factors, adding sets of subcomponents – the facets – to each factor. As an example, the TIPI result representation needs no more than the use of a set of factors, on the other hand the NEO-IPIP result needs not just the factors, but also the facets (vide section 3.2.1.).

### 5.2.1 Example of PersonalityML Syntax

The initial grammar was developed mainly focusing on the personality trait approach since it is the most used approach in Affective Computing as described before. Nevertheless it intends to be flexible enough to comport other approaches and theories than traits.

```

<personality>
  <approach name="Traits">
    <model name="Big-Five">
      <theory author="John A. Jhonson"/>
      <inventory test="NEO-IPIP">
        <factors set="Factors NEO-IPIP checks">
          <factor name="extraversion" score="42">
            <facets set="Facets NEO-IPIP checks">
              <facet name="warmth" score="62"/>
              <facet name="gregariousness" score="44"/>
              <facet name="assertiveness" score="13"/>
              <facet name="activity value" score="46"/>
              <facet name="excitement-seeking" score="60"/>
              <facet name="positive-emotions" score="42"/>
            </facets>
          </factor>
        </factors>
      </inventory>
    </model>
  </approach>
</personality>

```

Figure 1. Example of personality traits representation (Big Five Model) by using the PersonalityML.

Font: Devoped by authors .

(The entire schema, together to the complete grammar specification can be found at <http://www.personalityresearch.com.br/pp/index.php/en/products/software/personality/personalityml.html> )

### 5.2.2 Example of use

The scenario we thought for PersonalityML is that any person could use a computer or web application such as some personality inventory in order to discover his/her personality. Once the personality discovered and the prognostic generated, the personality aspects might be exported under the PersonalityML format. This personality data could, then, be used as input data for recommender system in e-commerce, e-learning, social matching, adaptative interaction and others applications.

Presently, the PersonalityML specification has been tested in some applications at Universidade Federal de Sergipe. These applications include (i) a personality inventory based on the NEO-IPIP and TIPI tests which extracts the user's personality through questionnaires and export it in PersonalityML format; (ii) a group recommender system which recommends work teams using individual's personalities as input data received under the PersonalityML format; (iii) a mobile movie recommender system, which infers the user's preferences about movies at geolocated cinemas based on his/her personalities and the user context.

## 6. Conclusion

In this paper we presented the steps towards the creation of a markup language to standardize the representation of personality in computers. Our initiative was to give an overview about how personality has been treated by Affective Computing scientists, giving the information concerning to where those studies started and how and why they were adopted by the recommender system area. We also described approaches more used to model, extract and represent personality, as well as strategies used by scientists to extract those aspects from user considering also other models already proposed by them. Finally we describe how we managed the construction of the structure of the PersonalityML followed by applied examples.

In addition, we emphasize we made some efforts towards to extend the human psychological metric representation by the standardization of personality by means of PersonalityML. Basedo on this initiative we intended to enable computers to use some defined pattern for representing personality to be used as social connections, social interaction and computer decision-making process, especially by personality-based recommender systems and personality-based web systems.

We also describe the PersonalityML initial grammar in order to standardize personality theories, putting our efforts as a drive force in order to make a public and usable mark-up language

technology intending to be complementary to the work developed by the W3C Multimodal Interaction Work Group.

We would like to highlight that in this paper, we presented an PersonalityML example only considering the most used personality approach, however we have already tested with some other, such as the Egogram, approach used by Minamikawa and Yokoyama (2011). As future work we intend to extend our studies and experiments to embrace another theories and approaches, as well to present our mark-up language to W3C.

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