MULTIDIMENSIONAL INTERESTS TROUGH AN ONLINE SOCIAL NETWORK SENSOR FOR SMART ENVIRONMENTS

Ricardo Barbosa [1*]
Ricardo Santos [2]

ABSTRACT

Online social networks allow users to socialise with others and also construct and manage their identities via self-presentation. Personality is strongly associated with human behaviour, is reflected and has impact on a user's online profile because people reveal their personality traits through their use of online social networks, who can be predicted with a relatively high accuracy. Smart environments need to successfully identify their user needs, personality and behaviour in order to prepare appropriate interactions when facing different types of events. Due to a constant presence in the lives of their users, online social networks can provide a rich source of data that can be used to profile and understand personal preferences and interactions of an individual. This creates a network of interests that is often represented by a single network that aggregates all of the connections. In this paper we propose a model for a multidimensional approach to this network of interests.

KEYWORDS: *Online Social Networks; Multidimensional Network; Personality Profiling; Self-presentation; Smart Environments*

1. INTRODUCTION

The presence of online social networks (OSNs) on our lives is incontestable and it is unrealistic to say that this is a passenger trend when the numbers speak for themselves. At September of 2016 Facebook leads the market with an astounding number of 1712 million active users, followed by WhatsApp and Facebook Messenger with 1000 million active users each, QQ (Chinese social media network) with 899 million and a little bellow we can find other popular social networks like Instagram and Twitter with 500 and 313 million active users respectively [1].

In order to successfully profile an user through his online social network activity, it is vital to understand the correlation between his personality traits and behaviour. Due to the strong impact of personality in human behaviour [2], personality is reflected and has impact on a user's online profile or activity [3]. Personality is a way for humans to describe themselves and others, and for decades, psychology researchers have worked to understand personality in a systematic way. After extensive work to develop and validate

[1*] corresponding author, Masters Student, CIICESI – ESTG|P.PORTO School of Management and Technology - Polytechnic of Porto, 8090242@estg.ipp.pt
[2] Professor Phd, CIICESI – ESTG|P.PORTO School of Management and Technology - Polytechnic of Porto, rjs@estg.ipp.pt

a widely accepted personality model, researchers have shown connections between general personality traits and many types of behaviour [2].

Ambient Intelligence and Smart Environments are impulsed by ubiquitous computing and take advantage of the ease of collecting data from numerous devices in order to produce tasks such as optimisation of energy consumption [4, 5], recognition of human activity and preferences [6, 7], aid the elderly or persons with health problems [8], or even increase the lifestyle of blind people [9].

We are now starting to look at OSNs in a multidimensional way rather than the plain single network that we are used to, and in this paper we propose a multidimensional model focused on the user's interests that can be useful for understanding user behaviour, patterns of usage, in order to provide smart environments with insights about their users, based on data extracted from their online social profiles.

This paper is structured as follows. Section two contains a brief definition of personality and its direct relation and influence in human behaviour, an explanation of the model used for personality traits classification and an overview about using text to extract personality. Section three presents the motivations that drives people to use OSN, and the concept of the need to belong and the need for self-presentation. Section four introduces the overall concept of multidimensional networks, how they are starting to be used on the social aspect of the OSNs, and the lack of multidimensional approaches to the interest network. Section five contains our multidimensional model proposition, the purpose behind the definition of each layer, the reasons and vision that motivate us to the definition of this model, as well as a conceptual example.

2. BEHAVIOUR AND PERSONALITY

The discussion of the existence of various personality types dates the time of Aristotle [10], but its definition is still ambiguous. However, most psychologists consider personality as a dynamic organisation, inside the person, of psychophysical systems that create the characteristics patterns of behaviour, thoughts and feelings of an individual [11]. D. Markovikj et al. [12] consider personality as a key component to identify a profile, and an uniquely identifier for each one of us which affects a lot of aspects of human behaviour, mental processes and affective reactions. Personality is an important factor in social interactions, some people are more talkative while others can be more shy, the same way that some can be more calm while others can be more insecure [13]. In essence, personal tendencies are shaped further through social interactions where individuals in a social network act similarly, sometimes referred to as normative (or normal) behaviour.

The way we talk, act, and write is different from person to person. A simple posture can express some insights about someone, and even when the content of a message is the same, individuals express themselves verbally with their own distinctive styles [14]. These same characteristics are also valid and can be found in written language, which is also unique from person to person. S. Adali and J.Golbeck [3] referred an important fact, behaviour is not simply a function of personality traits, but personality is an important trait that moderates people's behaviour and interactions with others.

The ability to predict personality has implications in many areas, existing research has shown connections between personality traits and success in both professional and personal relationships [2]. This profiling can contribute to understand the potential needs in different contexts [15] and it is beneficial for many activities on a daily basis such as customer support, recommendation of services and products and job applications [10].

2.1. Personality Classification

The ability to predict personality has implications in many areas, existing research has shown connections between personality traits and success in both professional and personal relationships [2].

Several well studied personality models have been proposed, however the Big Five model, introduced by Norman in 1963 [13] and matured by Goldberg [16], was established as the most popular one and is currently the most widespread and generally accepted model of personality [12, 2, 17]. The five dimensions can be described as the following:

- Openness to Experience: curious, intelligent, imaginative. High scorers tend to be artistic and sophisticated in taste and appreciate diverse views, ideas, and experiences (insightful vs unimaginative).
- Conscientiousness: responsible, organised, persevering. Conscientious individuals are extremely reliable and tend to be high achievers, hard workers, and planners (organised vs careless).
- Extroversion: outgoing, assertive. Friendly and energetic, extroverts draw inspiration from social situations (sociable vs shy).
- Agreeableness: cooperative, helpful, affection. People who score high in agreeableness are peace-keepers who are generally optimistic and trusting of others (friendly vs uncooperative).
- Neuroticism: anxious, insecure, sensitive. Neurotics are moody, tense, and easily tipped into experiencing negative emotions (calm vs insecure).

2.2. Personality Trough Text

Similarly to any order type of behaviour, the way we write can also be directly related with our personality. Some works approach this subject by content-based and style-based features [18] or by function words that may seem worthless but can actually tell a lot about someone [19].

Some successfully studies, like the one by J. Oberlander and A. J. Gil [20] and the work of J. Shen et al. [21] where they analyse the corpus of email messages and classified each user accordingly to the Big Five Model, proved the existence of personality traits in written text. Some characteristics mentioned by D.N.Chin and W.R. Wright [22] related to social media characteristics that are likely to affect personality include word length, author identification, grammar errors, topic and time-period bias, and even unusual syntax.

It is good to remind that different populations might tend to write about different topics as well as to express themselves differently about the same topic. A simple communication task like e-mailing a friend about recent activities, is likely to be accomplished differently by two people, depending on their recent experiences, age, geographic location, past experiences, character, or personality [20].

3. ONLINE SOCIAL BEHAVIOUR

Due to a constant presence in the lives of their users, OSNs have a decidedly strong social impact leading to a blur between offline and virtual life as well as the concept of digital identity [1] and the motivations for their usage differ from person to person, while some focus on broadcasting information about themselves others are more interested in passively consuming information produced by others [23].

OSNs not only permit users to socialise with others, but also offers the possibility to construct and manage their identities [24] by creating their visible profiles where is required, at a minimum, a name, gender and a date of birth. Among these required basic fields, users can add basic facts about themselves such as home town, contact information, personal interests, job information, and even a profile photograph.

When talking about personality classification based on OSNs, Ghavami et al. [13] work affirms that it is possible to avoid having the standard test scores in order to identify user personality by finding relationships between behaviour and personality, or even connection between an user’s network properties and personality. Data disclosed on OSNs can be used to make probabilistic inferences about socio-economic status, cognitive ability, life outcomes, cultural preferences, developed behaviours, average income, educational attainment, family size or even what genres of movies he is interested in [25].

Through the usage of ONSs individuals often express preferences for brands, products, services, persons, or even political preferences, in a free unsolicited way [26]. OSNs connect people who share interests and activities across geographic borders and have become a virtual mirror where users reveal a lot about themselves both in the way they share information and how they share it.

OSNs request that users construct truthful representations of themselves with varying degrees of accuracy [27]. Even demographic aspects can influence the type and frequency of usage, as an example, in their work K. Moore and J. C. McElroy [28] found a significant positive relationship between gender and a number of variables of interest where was possible to find that women spend more time on the OSN Facebook, had a greater number of friends, posted more photographs, and did more postings about themselves, when compared to men.

Accordingly to Nadakarni and Hofmann model [29] the motivation for the usage of a OSN is primarily motivated by two basic social needs, the need to belong and the need for self-presentation.

3.1. The Need To Belong

The need to belong is associated with the necessity for affiliation with others and the gain of social acceptance, since humans are highly dependent on the social support of others. Some type of obstruction from the social group have a negative impact in humans on a variety of health-related variables, including, self-esteem and sense of belonging, emotional well-being, sense of life meaning, purpose, self-efficacy, and self-worth [29].

G. Seidman [30] says that the need to belong is a fundamental drive to form and maintain relationships and a major motivator factor for OSN use. OSNs like Facebook allows users to fulfil belonging needs through communicating with and learning about others. Facebook can be an effective method for coping with feelings of social disconnection, as it enables peer acceptance, relationship development, and can even boost self-esteem.

3.2. The Need For Self-presentation

The need for self-presentation is correlated with the continuous process of impression management. OSNs opens the possibility for its users to display their idealised, rather than accurate, selves through their profiles [29].

Activities that accomplish self-presentational goals include posting photographs, profile information, and display relations. According to G. Seidman [30] popularity seeking users tend to disclose information, engage in strategic self-presentation, and enhance their profiles (that generally represent an accurate self-presentation).

4. MULTIDIMENSIONAL NETWORKS

M. Kivela¨ et al. study on multidimensional networks emphasis the increase on the study of networks with multiple layers, however that same explosion of studies produced a lack of consensus relative to the terminology. Their work presented a general definition of multidimensional networks (terms such as multi-layer network, multi-relational network, multidimensional network and multiplex network are considered synonyms [31]) that can be used to make a representation of most types of complex systems. In the real world, more than one kind of connections or interactions can exist between any pair of individuals, like friendship, family, or work, and accordingly to them, a multidimensional network has a set of nodes just like any normal network, and in addition there is the need to have layers that represent those types of different interactions that exist on the real world.

Despite not being new, the concept of multidimensional network [32] is fairly recent in the scope of OSNs and the work of A. Socievole et al. [33] makes reference to the effort that has been made into the definition of multi-layer social metrics that consider all the existing different social dimensions. Multidimensional approaches like the work of Brodka et al. [34] where they define a multi-layer social network as a set of single-layered social graphs with fixed set of nodes and variation on their edges. The work of M. Magnani and L.Rossi [35] proposed a multidimensional model where each layer corresponded to an OSN and a node mapping function between those layers. The work of A. Socievole et al. [33] presented a model with a routing protocol that makes use of multi-layer social networks to select nodes in order to act as message relays. The work of Forestier et al. [36] proposed a multidimensional social network from online discussions with relations derived from structure and text content.

5. PROPOSED MODEL

At the end of the 20th century, M. Wiser et al. work [37] described the existence of a new field of computer science created by ubiquitous computing, a field with a vision of a physical world filled with sensors, actuators, displays, and other computational elements, embedded on the objects of the daily life and connected through a continuous network. A vision of what we can recognise today as a smart environment.

Smart environments need to successfully identify their user needs, personality and behaviour in order to prepare appropriate interactions when facing different types of events, and in our previous work [38] we proposed a model for a sensor (or pseudo-sensor since usually a sensor is something physical) focused on obtaining insights about an individual's preferences, behaviour, and emotions, by using data extracted from his OSN profile. The usage of OSN as a sensor can provide additional information that would be missed otherwise, and takes advantage of the tendency of people and organisations to shift themselves into this virtual world.

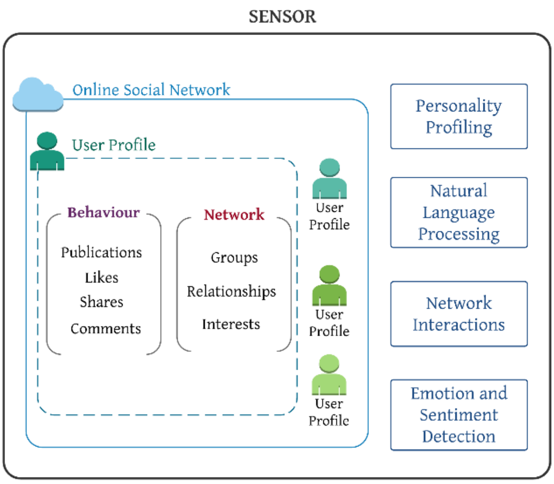

Figure 1. An online social network based sensor that uses online user behaviour and network references to profile an individual

This model, illustrated on figure 1, contains a heavy focus on the behavioural actions and the interest network that is present on an OSN. But when given the task of representing an OSN, generally it is shown as a graph and defined as a network of interactions and relationships, where the nodes consist of actors and the edges consist of the relationships or interactions between these actors [39]. Generally we end up with a 'unidimensional' network that considerate each different interest as the same and with the same level of personal affiliation, when often that isn't accurate. By dividing this entire network of interests into single layers it is possible to weight each type of action (for example by the effort required to produce each type of action), understand online behaviour, and even understand which type of interests are supported and reinforced by other layers.

Despite the effort made in multidimensional networks in the context of OSNs, those works are heavily focused on the social aspect and relations between users (the need to belong). Studies [24] have investigated the relations between OSN actions (like, share, comments, and similar actions) and offline behavioural intentions [40]. The usage of actions such as like, comment, and share can be represented as a way for users to manage their self-presentation by signalling their likes and dislikes, interests, preferences, and so on [24], and in this work we present a vision focused on the need for self-presentation, exploration of online actions, and the measuring of online content. Based on effort and type of actions, we divided the main network into three layers: association, interaction, and opinion.

5.1. Association Layer

This first layer contains the long term relations that can be found on most of modern OSNs, such as group associations, follows, or even subscriptions. We consider this associations as long term relations since they represent a higher permanent interest on a brand, people, or product, which can be seen as some kind of personal commitment.

5.2. Interaction Layer

The interaction dimension contains all of the less permanent types of actions such as likes (or similar action), or shares. In our vision, this type of actions is considered less permanent because of their ease and the less effort to perform. Like and share are a fast easy way to share content, they represent the user's appreciation and support for the content [24].

5.3. Opinion Layer

The opinion dimension refers to a network of opinions extracted from written text like comments, or any form of publication. This type of network is heavily focused on text analysis and requires some opinion mining techniques in order to extract positive or negative references. Due to this division, there are scenarios where this network can be divided into two layers, each one containing either positive or negative opinions. The text type of expression present on comments, and any form of publication, allows for a dynamic expression of thoughts and feelings with, usually, no restrictions to what is said [24].

5.4. Multidimensional Interests

Personality profiling can be helpful for the personalisation of an environment in function of his inhabitant, OSN for themselves are a good index to predict potential actions of users [39], and by dividing an user's interest network into layers it is possible to understand their preferences in an whole different level.

In figure 2 it is possible to observe a general representation of our model (with opinion layer was divided into two layers, each one containing either positive or negative opinions).

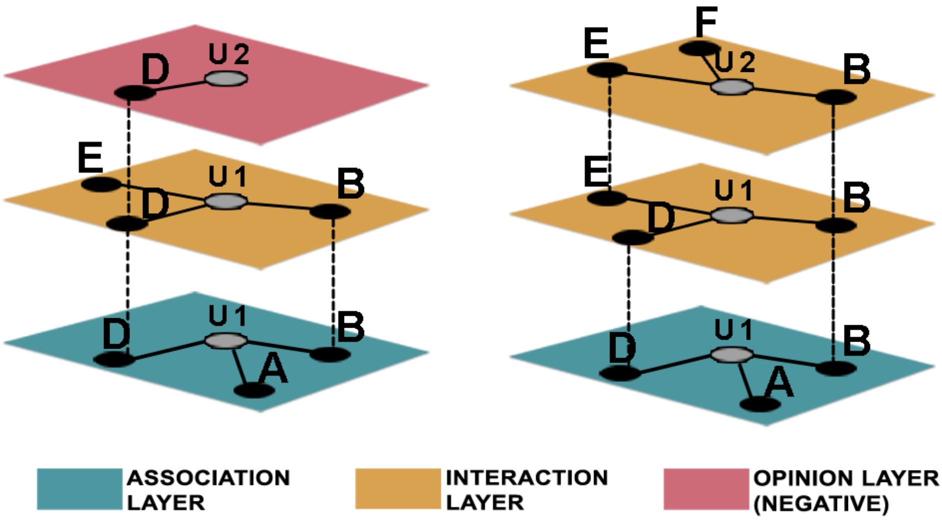

Figure 2. Multidimensional network representation of an users interest network

With this multidimensional approach to an user's OSN interest network, it is possible to understand behaviour and patterns of usage as well as defining weights to nodes. In this specific example it is possible to observe a heavily reinforced interest on the node 'B', followed by the interest on node 'D'. If both nodes 'B' and 'D' belong to the same topic (let's say music) in this approach is it noticeable the appreciation of node (or band) 'B' over 'C' which can be translated into a higher level of preference when comparing music bands. With this type of approach it is also possible to reinforce subjects, for example, if a new node 'C' is created on the Interaction Layer, it is automatically reinforced by the presence of the same node on the Opinion Layer. Since OSNs contain history of data about an user, we can use all of that data in order to aid smart environments to adapt in a more personalised way to their inhabitants.

Even with all of the information that we can obtain on the previous example, there might emerge the necessity of getting insights about some specific layers or even combining them in different. Since we are working in a multidimensional approach this is possible and we can have different layer combination or a creation of layers by type of content (for example music) in order to obtain a more detailed insight about a specific topic or on a desired context like understanding which topics or content an user does not like.

But we are not restrained to a single individual. Let's say for example that we want a smart environment (for example a room) to decide which type of music is playing based on the two (or more) people that are present at the moment. Like the real world, OSNs are not populated by an unique user and it is possible to combine layers of two (or more) different users in order to get insights depending on the desired context. Figure 3 contains a comparison between interests of two different users, we can observe a combination of their individual multidimensional networks in order to found similar interests (or even conflict of interests).

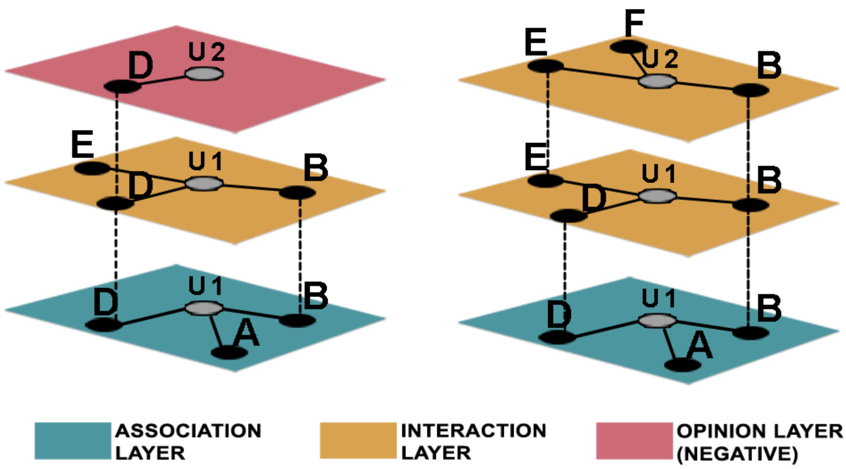

Figure 3. A comparison between two different users interests using multidimensional network layers

In this example it is possible to see, for example, that nodes of higher interest present on the network of the 'user1' ('B') are also an interest present on the 'user2' interest network (but with less impact), and we found another common interests on the node 'E'. We can also see that the 'D' node (or in this example, a music band) is not liked by 'user2' so the smart environment should avoid playing that music band. The result is an environment adapted around their inhabitant preferences and considering their negative expression about some topic.

But when we don't have enough data about some individual? What can we do? This type of problem is addressed by the personality similarities. Considering that our preferences are shaped and influenced by our personality traits, the environment can use history data about other interest networks that belong to people with similar personality traits in order to try to predict interests.

By approaching the interest network on a multidimensional vision, like our model, it is possible to combine different types and amount of layers and/or users, creating different types of dimensions based on our context needs, resulting in a more personalised environment without the need to ask for an input since that some of that data is often present on their online social profiles.

5.5. Limitations

According to the work of R. Wald et al. [23] users of social networking sites are becoming more aware of the information they post, and more concerned about how this information can be used to identify them. Most concerns related to social networking publications containing raw demographic information or specific offensively posts. For example, religious or political affiliation may impact on how an employer views a potential employee, as might an inflammatory post or salacious photograph.

It is important to notice, as pointed on D. N. Chin and W. R. Wright work [22], that the different social media outlets each have different characteristics that will likely affect their effectiveness for personality profiling and, for that reason, the multidimensional creation process may differ slightly depending on the desired OSN.

6. CONCLUSION AND FUTURE WORK

Personality takes a huge role in humans and it is a decisive factor that differentiates each of us in such a way that our actions and patterns are strongly connected to our personality traits. When looking at OSNs it is possible to observe that in a similar way, our online social behaviour is connected to our personality traits, and due to this fact their users share a lot of information about themselves and indicate many clues about their personality traits and preferences. From demographic information to overall interests and preferences, users liberally express themselves online in a free way, without any restrictions and this valuable information can be automatically fed to a smart environment to create a more personalised and responsive environment for his user.

Smart environments benefit for knowing the personal characteristics of his users and OSN can provide information that would be missed otherwise, however some of that information is often considered to have the same impact when it might not be the case. This consideration is due to the typical ’unidimensional’ representation of online interest networks, and in this work we explored the multidimensional approach to online interest networks in order to provide smart environments with more personalised and insightful data about their users.

Our next step is to simulate an environment using OSNs as sensors and approaching the users interest network in a multidimensional way in order to personalise and adapt the environment around him, as well as scaling this approach by including two or more users in the same environment and adapting the environment with the consideration of their common preferences and interests, as well as understanding any type of conflicts.

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