Human Behavior Understanding for Inducing Behavioral Change: Social and Theoretical Aspects

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Abstract. The 2nd International Workshop on Human Behavior Understanding (HBU'11) focuses on inducing behavioral change via computer systems that can analyse human behavior and communicate persuasive messages accordingly. While analysis techniques that involve pattern recognition, signal processing and machine learning are very relevant to this aim, the underlying psychological and sociological aspects of inducing behavioral change cannot be neglected. This paper provides a framework for assessing the impact of social factors for these applications, and discusses the role of social mediation of behaviors and attitudes.

1 Introduction

People routinely engage in relationships whereby they influence and are influenced by other humans but they are just starting confronting with machines that have this capability, due to the recent attempts at building persuasive systems. Most of the research on persuasive technologies is comprised under the umbrella of the term 'captology' [20], which refers to the study of machines designed to influence people's attitudes and behaviors. A notable difference between persuasion in human-human interaction as opposed to human-machine interaction, is the limited (if any) resort of machines to real-time understanding of people's individual traits, activities and social dynamics. As a consequence, most of the current persuasive systems lack flexibility and cannot personalize and adapt their message to the broader context the target person(s) is (are) in.[4]

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The automatic analysis of human behavior, in turn, has been progressing in the last few years, thanks to the shared awareness that computer systems can provide better and more appropriate services to people only if they can understand much more about their attitudes, preferences, personality, social relationships etc., as well as about what people are doing, the activities they have been engaged in the past, their routines and lifestyles.

This paper proposes a set of social and theoretical perspectives and considerations to develop systems and applications that rely on human behavior analysis for inducing behavioral change. These systems have the potential to re-define the relationship between the computer and the human, moving the computer from a passive observer role to a socially active one and enabling it to drive interactions that influence the attitudes and behaviors of people in their everyday environments [51].

In a quite general sense, the goal of this paper is to contribute to further advancing ubiquitous information societies where computers and humans are part of one and the same ecosystem. One crucial property of entities living in the same ecosystem is that they mutually influence and affect each other's behavior, as well as internal states (e.g., attitudes) in a host of different ways and through varied means, including implicit and indirect ones whose mechanisms are not necessarily fully grasped by the target.

It seems to us that there is still a good deal of reluctance in facing the puzzling possibility that, in order to approach autonomous human-like behavior, machines must, among other things, also be able to use different means to affect human behaviors and attitudes. Yet, this possibility is intrinsic to the overall vision of machines as autonomous agents in constantly changing environments, which lies at the heart of research areas such as artificial intelligence, cognitive systems, embedded systems, ambient intelligence, pervasive and ubiquitous computing, and so on. Such capabilities are also an essential ingredient of applications that aim to turn those technological and scientific advances into valuable services for the users.

This paper is structured as follows: Section 2 proposes a possible approach to social influence and computer-induced behavioral change. Section 3 deals with the possibility of endowing machines with the skills needed to social perception, and underlines the importance of personality assessment. Section 4 shortly discusses the sensing modalities for social behavior, and provides pointers for further reading. Section 5 discusses the technological, scientific and societal impact of the discussed framework. Finally, the last section draws our conclusions.

2 Bringing about change: perspectives on social influence

In an attempt to lay the foundations of a theory for computer-induced human change, we will operate under several assumptions that incidentally set this work apart from most current efforts in the same direction. First of all, our focus is on the modifications of the social structure and dynamics of small and large groups (friends, colleagues, families, students, and so on) and on changes in individuals (behaviors and attitudes) that occur because of their membership in social entities. Social settings are, in most respects, more challenging than those based on a single individual because of the dynamic and bidirectional individual-group relationships: in many respects, understanding a group's characteristics implies understanding the characteristics of its members, and social change implies individual change.

In social psychology, researchers study the psychological processes involved in persuasion, conformity, and other forms of social influence, but they have seldom modeled the ways influencing unfolds when multiple sources and multiple targets interact over time [43]. On the other hand, researchers in sociology, economics, network science and physics have developed models of influence flow in populations and groups without relying on any detailed understanding of the participating individuals. For example, the social diffusion phenomenon, in which a behavior spreads over a social network, is explained by a mechanism of behavioral cascading whereby the probability for a group member to adopt a behavior is affected by the adoption behavior of the other group members. In many aspects, this approach is similar to a popular model of spreading epidemics: subject X adopts the same behavior as the other group members if his/her exposure to it exceeds a given threshold [10, 13, 24, 57]. Obviously, at this level of modeling, details of individuals are neglected.

Recently, some proposals have been advanced to incorporate a detailed micro-level understanding of influence processes derived from social psychology within the broader picture of multidirectional, dynamic influences typical of social network studies [43, 21]. For example, Friedkin proposed to merge social-psychological approaches to the attitude-behavior link with the behavioral cascades diffusion models [21]. The attitude-behavior link, in turn, is accounted for by means of the Theory of Planned Behavior (TPB) [2]. In a simplified form, TPB maintains that actual behavior is explained by behavioral intentions that, in turn, are influenced by (i) the specific attitudes toward that behavior (e.g., attitude towards smoking); (ii) subjective norms (beliefs concerning how the people one cares about view the behavior in question); and (iii) perceived behavioral control (e.g., whether people think it will be easy for them to stop smoking).

Once the relationships from attitudes to behavior is accounted for, the reverse link, from behavior back to attitudes, can be modeled using, e.g., the Self Perception Theory (SPT) [8]. According to SPT, the behavior-attitude link is activated in situations where people do not already have clear ideas about their own attitudes, so that they rely on external observations to infer about then. For instance, STP's view of the behavior-attitude link fits well situations in which individuals' attitudes are not yet well formed.

Another possible shift in the conception of computers as actors of social change is the idea that they behave as a sort of peripheral device, exploiting different kinds of minimalist strategies to bring about change through the smallest amount of human-computer interaction. Minimalist strategies are motivated by the desire that even in the presence of a change inducing system, the main activity of people (their 'primary task') remain that of interacting with other people (e.g. friends, colleagues, relatives, and so on). Minimalist strategies for change could exploit the accumulating evidence about behaviors occurring automatically and without conscious effort [5, 11]. For instance, people who were unconsciously exposed (primed) to the stereotype of an elderly person walked slower than a control group [6] and participants listening to male-typical words while driving drove faster than participants listening to neutral words [54]. Importantly, direct investigations about the participants' perception of their own behavior revealed that they were not aware of these induced changes.

Because of its pervasiveness, the so-called direct perception-behavior link [11] can be exploited to bring about desired behavioral changes by means of priming procedures (based on gender-related, cultural, age-related, etc., stereotypes) and/or by facilitating *mimicry*, the tendency to mimic other individuals' behaviors without awareness or intent. One might also venture that at least some of the phenomena usually addressed under the rubric of *behavioral cascades* and *social contagion* (i.e. the propagation of behaviors and attitudes in a socially mediated manner) can be profitably addressed by means of the concept of mimicry and of the perception-behavior link.

The idea of agents that pursue change through indirect and minimalist strategies is also related to the peripheral route to persuasion of the Elaboration Likelihood Model (ELM) [46]. This often-discussed socio-psychological model of behavioral/attitudinal change posits two ways in which attitudinal and behavioral change can take place: a central route and a peripheral route, respectively. The **central route** requires that the influencee attentively attends to an argumentative communication and thinks about the arguments presented. The efficacy of this communication depends on the coherence, logic, and depth of the arguments presented, as well as the knowledge and reasoning abilities of the receiver. The **peripheral route**, in turn, involves strategies that influence people by means of peripheral cues, e.g., the status of the communication source, its attractiveness and credibility, etc.

Some recent works have attempted at exploring these ideas by devising systems that present members of a working group with information about their own social behavior, with the goal of changing it and making it more conducive to better group dynamics [16, 33, 47, 56]. Moreover, an interesting and recent work [1] tested an experimental intervention for inducing changes in fitness-related, physical activities and habits. The intervention was based on a novel social mechanism in which subjects were rewarded based on their peers' performance rather than their own. The results suggested that (i) social factors have an effect on physical activity behavior over time, (ii) social incentives strengthen social influence among subjects, and (iii) a phenomenon similar to contagion emerges as it relates to the pre-existence of social ties among the subjects. This work is a good example of the way two of the general concepts discussed so far can work to drive behavioral chenges: (i) the importance of social factors in inducing individual changes and (ii) the effectiveness of strategies based not on argumentation and logical reasoning but on mimicking and learning through imitation of the others' behavior.

3 Understanding social behavior

From the discussions of the previous section, two major dimensions emerge that characterize change in our framework: (i) social vs. individual change and (ii) attitudinal vs. behavioral change.

Regarding the first dimension, we pursue both social and individual change, with the latter addressed through the mediation of the group. It therefore pops up with all its importance the goal of endowing behavior-inducing systems with the ability to understand social behaviors and social relations.

It is impossible to mention here the many cognitive and social psychology theories that have been formulated to account for human social behavior. It is more important to point out that some of these theories are already providing the backbone to computational models and are going to be used in change-inducing systems. A telling example in this respect are dominance and other dimensions related to social verticality [22]. Dominant behavior, in fact, is a key determinant of a group's social structure and dynamics [7]. Quite straightforwardly, the recognition of dominant people could be useful to decide about the right subjects to address in order to maximize the chance of success of group persuasion attempts.

Following the lead of much work in social psychology [25, 44], computer scientists focused their attention on studying dominance and role-based status cues [27, 28, 31, 49, 50] and functional social roles [59, **?**] in small-group, task-oriented meetings, using audio-visual nonverbal

Another important piece of knowledge that can be used to to build effective change-inducing systems is personality: people, in fact, react differently to persuasive stimuli according to their personality. For instance, studies about the relationship between the trait of self-esteem and susceptibility to social influence have reported that people with low self-esteem are most easily influenced and those with high self-esteem are much less so [29, 30]; other works found that people with medium self-esteem values are most open to influence [26, 14]. Locus of Control, too, has been found to empirically relate to social influence susceptibility. *Internals*, who believe they control their behavioral outcome during their lifetime, seem to be more resistant to social influence than *externals*, who attribute their behavioral outcome to external factors such as fate, luck, or powerful others [26, 14].

Moreover, the relative efficacy of one or the other persuasive route in the ELM model might also depend on the personality of the target subject: for instance, people who are deemed as "in need for cognition", a trait indicating that people enjoy thinking about complex problems [9], are more amenable to persuasion through the central route than people who score low in such a trait [9, 46]. Conversely, people with low need for cognition are more susceptible to be persuaded using unconscious stimuli (e.g. mimicry and priming strategies).

On the computational side, several works have started exploring the automatic recognition of personality, mostly targeting the Big Five model [41, 42, 37, 36, 47, 12] and/or traits such as the Locus of Control [36, 47], using different sources of behavioral data, e.g. visual and acoustic cues and mobile phone data. All these approaches to the automatic recognition of personality more or less implicitly share the so-called 'person perspective' on personality [19]: for a given behavioral sample, they attempt to classify whether that sample belongs to an extrovert or introvert (or equivalently, to a neurotic or an emotionally stable person, and so on). The problem with this approach is that it assumes a direct and stable relationship between, e.g., being extravert and acting extravertedly. Extraverts, however, can sometimes act introvertedly, while introverts can at times exhibit extraverted behaviors. Similarly, people prone to neuroticism need not always exhibit anxious behavior, while agreeable people can sometimes be aggressive. While the person perspective has often dismissed these fluctuations of actual behavior as statistical noise, it has been recently suggested by Fleeson [19] that they can be meaningful. The social psychology literature has coined the term *personality states* to refer to concrete behaviors (including ways of acting, feeling and thinking) that can be described as having a similar content to the corresponding personality traits. In other words, a personality state describes a specific behavioral episode wherein a person behaves more or less introvertedly/extravertedly, more or less neurotically, etc. Personality can then be reconstructed through density distributions over personality states, with parameters such as means, standard deviations, etc., summarizing what is specific to the given individual. Recently, this paradigm shift has started being considered by computational approaches, as by Staiano *et al.* who investigated the automatic recognition of personality states in small group meetings [55].

Regarding the second dimension, a change inducing system could aim to modify individual minds by changing their attitudes towards the relevant issues (or person, group of people, etc.). It might also try to change people's behavior directly. We note that the distinction between mental and behavioral modifications is not unlike the differences in effect durations; mental modifications last longer than those that affect only behavior.

Recently, some works started to model behavioral and attitudinal changes in individuals [38, 40, 39]. In [40], the authors described the use of mobile phones to model and understand the link between exposure to peers and weight gain among a group of undergraduate students, where a positive correlation was established between the change in an individual's Body Max Index (BMI) with face-to-face exposure to social contacts who themselves gained weight. Along the same direction, Madan et al. [39] measured the spread of political opinions (republicans vs. democrats) during the 2008 US presidential election campaign to model specific behaviors and changes in political opinions.

4 Sensing social signals

The previous section showed that we can endow machines with the skills to understand and predict human social behaviors, individual characteristics and attitudes. In this section, we reviews ways we can provide them with the ability of perceiving and sensing the social signals upon which such an understanding can be built. Research on first impression formation has demonstrated that even when observing a person in social interactions for only a short amount of time and even without knowing him/her, we are capable to accurately assess aspects of his/her personality [3, 23], emotions, motives and intentions, cognition, future behavior and the types of social relationship he/she is used to get involved in [53, 25]. This quite precise "zero-acquaintance" appreciation (or rapid cognition) of the internal properties of another person is based on short sequences of expressive behavior called "thin slices of behavior" [4], is almost automatic and largely exploits nonverbal behavior [3, 32], such as posture, position, facial expressions, location, prosodic features, and so on.

There is encouraging evidence that computers can be made capable of exploiting thin slices of behavior to detect individual traits such as personality [35, 47] and dominance [27, 28, 31], group properties like social roles [17], interactions' outcomes [15, 36], etc. Many of these works have employed so-called 'honest signals' - social signals that, being too difficult for humans to control, can provide a reliable source of information about socially relevant aspects [58, 45].

In [51], the authors have discussed the different modalities used to sense signals pertaining to individual behavior or social behavior. Traditional sensors like cameras and microphones provide valuable information, yet sensing social data almost invariably is more challenging than sensing the behavior of a single individual, and temporal dynamics is found to be of the utmost importance for social signals [52]. For instance turn-taking behavior, interruptions, relative sound energy, usage of gaze and attention, are all found to be relevant in transmitting status and dominance [22].

Recently, the rich sensor sets installed in smartphones have been harnessed to transform the smartphone into veritable data mines for assessing social interaction information. Not just the usage patterns of these phones (as in the reality mining study of Eagle and Pentland [18]), but also proximity and communication data have been found to be useful [38, 40, 39]. Other types of sensors have been packaged into wearable units, the so-called 'sociometric badges', to specifically target small-group interactions [34].

These developments allow for a cost-effective, real-time, extensive, and (mostly) unobtrusive monitoring of human social signals, and open up the way to the implementation of new socially sensing machines.

5 Technological, scientific and societal impact

The framework proposed here contributes to transform science, technology and societies in several different ways, and it is difficult to underestimate the societal impact of computer systems that induce behavioral change. Such systems can contribute to enforce individual and social values by helping individuals reach target behaviors through interaction and immersion. Apart from technological challenges, these systems require careful preservation of privacy and the maintenance of appropriate levels of control by the users. The enormous potential impact is partly due to the ubiquity and informality of such systems; they can be everywhere and can function through subtle and inconspicuous influences.

It is also due to the richness of the application domain, as these technologies stand to transform vital sectors such as healthcare, organizational and individual psychology, management, education, entertainment, commercial advertising, politics, and many more. The societal impact will not be limited to the offer of new and revolutionary technologies, as the relationship between systems and users will change in fundamentally different ways. Once the ethical and legislative framework is set in place, researchers from different fields will have access to first hand, empirical data on how computer-induced change works in realistic contexts, as well as models and paradigms to initiate new projects of behavioral change.

The marriage between social sciences that systematically chart out principles of human behavior and computer-related disciplines (such as multimodal analysis, signal processing, pattern recognition, machine learning) that aim to provide computer systems with the ability of automatically analyzing behavior, can produce long-lasting effects on both sides. Social psychology and social sciences have worked out much of the theoretical foundations for the issues discussed in this work. However, present approaches like TPB, thin slices in rapid social cognition, the perception-behavior link, peer pressure, social contagion, etc., are mostly descriptive frameworks that lack formal and computational modeling. The framework proposed in this paper is mostly geared towards laying the foundations of computational modeling of psycho-social and sociological concepts and theories with the goal of actually incorporating them in working real-world systems.

The combination of psychology and technology at this level is a major departure from the tradition and practice of captology. Although the Computer as a Social Actor (CASA) framework [48] has convincingly argued that we tend to attribute computers characteristics that are typically human, it has done so in quite restricted scenarios, mostly limited to single computer-single human settings. The tradition of captology has taken the media equation and CASA as enabling factors for computer-induced change. By exploiting concepts such as the peripheral route to attitude, the automaticity of behavior, the peer pressure of cascade models, we depart from this tradition, requiring forms of sociality in the human-computer relationship, and subsequently filling a gap in our understanding of the social/non-social continuum in human-machine interaction.

6 Concluding remarks

Throughout the paper, we have been stressing the importance of social and personality factors for building systems that interact with individuals in ways that would result in behavioral change. When we design 'persuasive' systems, the dialectic nature of human-computer interaction cannot be ignored, and we converge, in many respects, onto models of human-human interaction, i.e. the twin domains of psychology and sociology.

The influencing of a single person can happen via different routes. It is possible to directly influence a certain behavior, or to cause changes in an attitude that will in time result in the modification of a certain behavior, or start a behavioral cascade, where the behavioral change in the individuals social circle (for instance through the dominant people in the group) will eventually cause the individual to adapt to its environment by accepting the same behavior change. The persuasive message can require conscious processing and elaboration, or it may be subliminal and peripheral. We have cited many empirical studies, which establish that there is no general methodology that can be adopted for persuasion, but each individual will, depending on his or her personality, his or her context and other such factors, be influenced by different strategies to differing extents.

A point of consideration is that even very short expressions of behavior can be extremely useful in selecting the appropriate strategies. These cues can give us the key to detecting dominant people in groups or personality traits of interacting individuals, thereby laying the foundation for inducing behavioral change. Old and new sensor technologies are combined in innovative ways to capture these social signals. It is our firm belief that the resulting systems will have a significant impact on the confluence of humans and computational systems.

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