Human Behavior Understanding for Inducing Behavioral Change: Application Perspectives

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Abstract. Pervasive sensing and human behavior understanding can help us in implementing or improving systems that can induce behavioral change. In this introductory paper of the 2nd International Workshop on Human Behavior Understanding (HBU'11), which has a special focus theme of "Inducing Behavioral Change", we provide a taxonomy to describe where and how HBU technology can be harnessed to this end, and supply a short survey of the area from an application perspective. We also consider how social signals and settings relate to this concept.

1 Introduction

In recent years, the automatic analysis of human behavior has been attracting an increasing amount of attention from researchers because of its important potential applications and its intrinsic scientific challenges. In many technological fields (pervasive and ubiquitous computing, multimodal interaction, ambient assisted living and assisted cognition, computer supported collaborative work, user modeling, automatic visual surveillance, etc.) the awareness is emerging that a system can provide better and more appropriate services to people only if it can understand much more about users' 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 life-styles, etc.

At the same time, several attempts have been made to build *persuasive technologies*. Most of the research on this topic is often comprised under the umbrella of the term 'captology', which generally refers to the study of machines designed to influence people's attitudes and behaviors. The challenge in captology is to design an engaging and stimulating environment (or technology) that in time would steer the user's behavior towards a desired behavior. In [15], Fogg stresses the distinction between a technology's side effects and its planned effects, where the latter is relevant from a design perspective. For instance, exposure to violent video games may increase aggressive thoughts, feelings, and behaviors, and decrease helping behavior, as unplanned side effects [2]. Although a better understanding of the mechanisms underlying side effects would make it possible to compensate for them, it is the planned effects themselves that have been attracting most of the attention.

Current efforts towards persuasive technologies have rarely taken into account the real-time understanding of individual traits or the social dynamics the users engage in. Technologies for human behavior understanding (HBU), however, can be gainfully employed to make these persuasive systems more context-aware, interactive, adaptive, immersive and even anthropomorphic. The goal of this paper is to give an application perspective on how to reach these goals. Since persuasion is not always an explicit goal of such systems (as we will show later via examples), the systems we describe here span a broader area than "classical persuasive technologies.

This paper is structured as follows. Section 2 describes taxonomies for employing HBU in a persuasive environment. Then, Section 3 reports recent research focus in different pervasive sensing modalities. Section 4 gives application examples for inducing behavior change, selected from four different domains. Finally, Section 5 concludes the paper. In this work, we are not going to discuss the theoretical and social aspects of behavioral change; these are tackled in a follow-up paper explicitly dealing with these issues [33]. In the present volume, [30] gives a good overview of theories on behavior change.

2 Taxonomies

In this section we discuss where and how HBU can be employed to induce behavioral change. We should note here that in computer science, the term "behavior" usually refers to a relatively short, measurable pattern of activity, whereas in psychology, it incorporates a broad range of details, pertaining to ability, intentions, and sustainability. The construction of relations between different time scales is one of the challenges in this area. By Human Behavior Understanding (HBU), we mean here pattern recognition and modeling techniques to automatically interpret complex behavioral patterns generated when humans interact with machines or with other humans [51]. These patterns encompass actions and activities, attitudes, affective states, social signals, semantic descriptions, and contextual properties [52]. Since persuasion is a detailed framework for discussing how to induce behavior change, we will adopt it as our main guideline, and deviate from it only occasionally.

Technology can achieve persuasion by being a tool (improving abilities, providing customized information, guiding people through a process, etc.), by being the channel of persuasion (particularly relevant for ambient intelligence (AmI) scenarios, where the environment uses feedback and visualization to provide behavior changing experiences) or by being a social actor to persuade through social communication channels [15].

Adapting the terminology of the attitude change model of Petty et al. (1997) [46], consider a **source** that sends a persuasive **message** (here a computer system with some output) to a **recipient** of the message (a human). HBU technologies can play different roles in this processes:

- **Positioning:** The source uses HBU to position the recipient, and selects appropriate messages (e.g. identifying whether the source has an attitude with a cognitive or affective base to select appropriate arguments [46]).
- **Feedback:** The source uses correct feedback towards sustaining behavior (e.g. monitoring facial expressions to judge the effect of provided messages).
- **Message:** The result of HBU is a part of the message to the recipient (e.g. measuring activity levels and visualizing them for a fitness application).
- **Evaluation:** HBU measures the progress of the recipient (e.g. a sign-language tutoring tool evaluating the correctness of replicated signs).
- **Prediction:** HBU is used to predict future behavior, to allow the system to adapt and preempt (e.g. predicting when the user will engage in harmful behavior and providing a timely feedback to prevent it).
- **Social guide:** HBU is used to increase the credibility of the source (e.g. an embodied conversational agent observing social norms and responding coherently to the social signals of the receiver). Correct display and interpretation of social signals play a great role in the persuasiveness of a technology.
- **Immersion:** HBU facilitates the construction of an immersive system, where the target behavior is encapsulated in the interaction with the system (e.g. a body movement and gesture based fitness game).

Fig. 1 shows some of the potential contributions of HBU in inducing behavioral change. Initially we consider the traditional case of a source, a message, a channel and a recipient. Broadly, HBU can be used for the analysis of social and affective cues to provide a better model of the context for the message. It can also be used to scale up assessment by eliminating a resource bottleneck: Most persuasive technologies are assessed by questionnaires, and other manually performed assessment tools. While these technologies are not widely adopted yet, real-time assessment is conceivable for applications where the effects of induction is not otherwise easy to observe directly. To give a simple example, we can monitor cigarette sales, but HBU can give us the number of actual instances where a subject lights a cigarette.

The most important contribution of HBU seems to be in improving **the message**. Learning recipient behavior can tell the system something about the response patterns of the recipient, and help message selection. It can also help message timing via prediction of certain behaviors. If the system can tell when the driver is going to speed, it can provide a timely message to negatively reinforce this behavior. The second contribution is to observe the recipient and make behavior-related cues part of the message. For instance, your energy consumption can be visualized for you in green or red light, prompting you to reconsider your consumption habits [23]. Thirdly, HBU can help transform the singular message into a communicative exchange. A successful embodied conversational agent (ECA) is an engaging conversation partner, and such tools can effectively

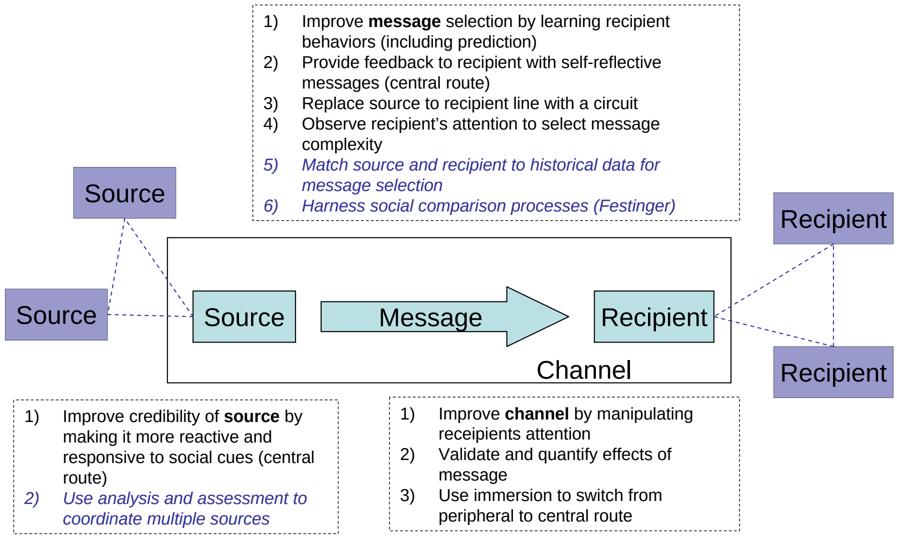

Fig. 1. Points of contribution for HBU in inducing behavioral change. Potential contributions to source, message and channel are listed. The case of multiple sources/recipients is indicated with blue italic lines.

engage more cognitive resources (i.e. from the perspective of the elaboration likelihood model [45], they engage the *central route*, as oppposed to the *peripheral route*[1]). Through HBU, social interactions with systems can be augmented to pay attention to dimensions like empathy and intimacy, and thereby more natural interfaces can be obtained [21].

If the system has several messages, HBU can help in selecting the most appropriate of these. In a multiple source/recipient setting (i.e. a social setting), previous message exchanges and their observed results can serve as templates, and help in message selection (e.g. recipient A resembles recipient B, who responded well to message X, so the system follows the same strategy). Finally, observed behavior of multiple recipients can be used to mutually improve all messages sent to these recipients by harnessing social comparison processes.

The channel can benefit from HBU as well. The archetypical examples come from the ambient intelligence setting. It is possible that the environment observes the recipient's current focus of attention (e.g. by gaze tracking or speech analysis) and improves message delivery. Such an environment can potentially track

[1] According to the elaboration likelihood model (ELM) of Petty and Cacioppo, there are two different routes for changing the attitudes and the behaviors of a person, namely, a central route and a peripheral route, respectively [45]. The central route assumes attention to and elaboration of arguments, and involves coherence, logic, and clarity of arguments. The peripheral route, on the other hand, use secondary attributes like the attractiveness of a source, its familiarity, credibility, etc.

the 'progress' of the recipient in an unobtrusive way, and quantify the effects of the message. [25] is an excellent discussion on persuasion in ambient intelligence settings, where the authors discuss many principles of human persuasion that may have repercussions for computer persuasion systems. The paper also introduces the *ambient persuasion model*, where a distinction is made between a horizontal axis of change (to model messages from a source to a recipient), and a vertical axis of change to model the temporal aspects of change, where short (the initial attitude), medium (behavior) and long-term (sustained behavior) effects are considered. Such a vertical axis of induced behavior duration is also proposed by Fogg, where the shortest change is a one-time performance of a behavior, and the longest change is a change of habit [16].

The channel can also offer an immersive experience and thus effect message processing. A conversation with an ECA where the recipient is manipulated to argue for a certain message can be effective, since through immersion more central, cognitive processing of the message can be ensured.

HBU can improve **the source** by increasing its credibility. This can be achieved for instance by making the source more responsive to social and affective cues observed in the recipient. An application example would be an ECA that acts as a source. Analysis of the recipient can make the ECA more plausible, as it conforms to social signals, observes backchannel rules, etc. In the multiple source case, HBU can be used to coordinate messages from different sources. For instance, if the messages are given in different modalities, or at different locations, the user behavior can be monitored to coordinate the messages.

In general, the use of HBU and the consequent modeling and understanding of social dynamics, individual traits, internal states, attitudes, and routines are able to contribute to a more ambitious goal, namely the design and construction of machines that act as social actors and that are able to purposely influence the attitudes and the behaviors of people in their everyday natural environments.

3 Pervasive Sensing

What kinds of behaviors can we analyze with HBU technologies? The answer to this question partly rests on the sensory modalities that we are willing to deploy, and the amount of computational resources we are willing to devote to observe and model humans in particular environments and contexts. To summarize, we can sense:

- **Specific behaviors:** Visual and auditory actions, activities and complex behaviors.
- **Psychophysical signals:** Bodily signals, physiological measurements.
- **Activities:** Amount of performed behavior per time unit, including body, head and facial movement, amount of speaking, and any other virtual and real behaviors.
- **Engagement:** Visual attention and gaze patterns, postures and gestures indicating engagement, speaker turn-taking behavior, indications of interest and motivation.

– **Empathy:** Mirroring and mimicry of speech and gestures, signals of agreement and disagreement, physiological signals of affect and empathy.
– **Other social signals:** Social role indicators, voluntary and involuntary social signals.

It is possible to group the research activity on HBU around sensory modalities.

3.1 Vision and audio

The visual modality has traditionally been the primary channel for deriving information about human behavior at different scales. The whole gamut of spatio-temporal scales of behavior are explored with visual modalities. In the present volume, Hadid gives a broad overview of facial behavior analysis, which can occur over very short time frames, and can involve barely noticeable muscle movements [18]. On the other end of spectrum, cameras and camera networks can be used for monitoring multiple subjects. [10] use vision for tracking multiple subjects in an indoor scenario, and detect dyadic interactions. At an even larger scale, [48] describes an approach for detecting abnormal behavior in a crowd. In between, we find for instance analysis of hand gestures, which can have a rich vocabulary and thus pose a challenging classification task. In the present volume, [27] shows that a clever pre-processing stage can greatly improve the recognition of hand gestures.

Recent methods for gesture recognition involve the use of RGB-D cameras (e.g. the Microsoft Kinect), if the distance requirements of the RGB-D camera is met in the application [28]. The 1^{st} IEEE Workshop on Consumer Depth Cameras for Computer Vision (CDC4DV)[1], organized as a satellite to ICCV'11, received over 60 submissions, which is a clear acknowledgment of the great potential of this modality. Among the contributions of CDC4CV, we note a novel color-depth video database for human daily activity recognition [40], and new pose detection approaches [20, 9]. Also for robotics applications, RGB-D cameras have quickly become the standard for estimating the pose of interacting humans, as we have witnessed in the RoboCup@Home competition in 2011[2]. In [32], such a camera is used to combine pose and motion cues to detect change during human-robot interaction. The system allows the robot to imitate the gestures of the interacting human, which is particularly useful in turn-taking for cases where the semantics of the gesture performed by the human is not precisely understood by the robot.

Apart from new modalities, progress in image retrieval techniques have also resulted in improved camera-based identification of actions and activities, as well as recognition of events [56]. The shift is towards learning the temporal aspects of activities, and generalizing from limited amount of training data [43]. In the present volume, Baccouche et al. propose a two-stage model for action recognition, where convolutional networks are extended to 3D case for learning

[1] http://www.vision.ee.ethz.ch/CDC4CV
[2] http://www.robocupathome.org

spatio-temporal features, followed by a recurrent neural network that classifies sequences into action classes [4].

HBU research in auditory modality focuses on the classification of paralinguistic information, including speaker states like affect, intimacy, deception, sleepiness, stress, etc., as well as speaker traits like gender and personality. Additional vocal behavior like yawns, laughter, and other vocalizations are automatically classified as well. Schuller provides an overview of this area in [55].

3.2 Mobile phones as social sensors

Recent developments in mobile technologies and the advent of the smartphones have opened the way to a new and very useful tool for social sciences, particularly sociology, social psychology, urban studies, and network science. Smartphones allow for unobtrusive and cost-effective access to previously inaccessible sources of data related to daily social behavior [47, 31]. The most important feature of a smartphone is its sensing ability. Nowadays, these devices are able to sense different kind of behavioral data: (i) location, (ii) other devices in physical proximity (e.g., through Bluetooth scanning); (iii) communication data, including both the metadata (logs of who, when, and duration) of phone calls and text messages (SMS) as well as their actual contents (e.g., recording of voice and text of SMS); (iv) scheduled events, (v) the devices status (e.g. network coverage, alarm clock, charger, status, and so on), (vi) movement patterns, and (vii) the user interaction with the mobile phone (e.g., the user is downloading some application; he/she is engaged in a call, is surfing the web and/or browsing a specific page; he/she is playing games, etc.). Additional sensors can provide researchers with futher useful information: detailed locations using a GPS, actions and activities by means of accelerometers, physiological variables (e.g., heart rate, galvanic skin response).

One of the first approaches for modeling human behaviors from mobile sensor data was the Reality Mining study [14]. In this work, the researchers followed 94 subjects using mobile phones, recording data about (i) call logs, (ii) Bluetooth devices in proximity of approximately five meters, (iii) cell tower IDs, (iv) application usage, and (v) phone status. Subjects were observed using these measurements over the course of nine months. The researchers also collected self-reports about relational data from each individual, where subjects were asked about their proximity to, and friendship with, others. Subjects were also asked about their satisfaction with their work group. This study compared observational data from mobile phones with standard self-report survey data, finding that the information from these two data sources is overlapping but distinct. For example, self-reports of physical proximity deviate from mobile phone records depending on the time difference and salience of the interactions.

Mobile sensor data have been used to understand a broad spectrum of sensing and modeling questions. Some examples include automatically inferring of co-location and conversational networks [59], linking social diversity and economic progress [14], automatic activity and event classification for mass market phones [38], and the adoption and diffusion of applications [44]. In particular, three recent studies exploited mobile phones to model behavioral and attitudinal changes in individuals [34, 36, 35]. In the first study [34], proximity and communication data are used to improve the understanding of the link between behaviors and health symptoms at the individual level. In particular, this study demonstrated the existence of characteristic behavioral changes in subjects suffering from common diseases like colds, flu and stress.

In the second study [36], the authors described the use of mobile phones to model and understand the link between exposure to peers and weight gain among students during the course of a semester. This study demonstrates that the change in an individuals Body Max Index (BMI) can be explained by face-to-face exposure to contacts who themselves gained weight.

In the third study, mobile phones were used to measure the spread of political opinions (republicans vs. democrats) during the 2008 US presidential election campaign between Obama and McCain [35]. Mobile features in term of proximity can be used to estimate unique individual exposure to different opinions. Furthermore, the authors proposed a method to understand the link between specific behaviors and change in political opinions, for both democrats and republicans. In particular, they used the Latent Dirichlet Allocation (LDA) topic model [6] to contrast the activities of participants who changed opinions with those who did not.

3.3 Wearables, brain-computer interfaces, and other sensing devices

Physiological reactions can provide insight into subjects' affective states. These are typically galvanic skin response, heart rate, palmar sweat, pupillary dilation and constriction, and such. These need to be worn on the body, which means they are intrusive to different degrees. This, however, may not be a problem in certain settings, especially in working environments where special dress and equipment needs to be used. In [39], nurses and physicians in a stroke unit of a hospital were equipped with wearable electrocardiography (ECG) and acceleration sensors to measure the amount of stress they experience during their everyday work. The identification of and feedback about stressful situations can lead to avoidance behavior for these situations.

Nijholt et al. provide a survey of approaches that use brain-computer interfaces for innovative applications, among which we find many instances of inducing behavior change [41]. They have elsewhere demonstrated how one can control a character in the popular video game World of Warcraft, with the brain. They analyze the brain activity for alpha waves (in the frequency band of 8-12Hz), which relates to relaxed alertness, and allow the game character to change into a bear when the actual character is under stress. An earlier example is the Brainball game, where two gamers have to control a ball on the table by remaining calm [19]. In both cases, waves of the brain are sensed by a portable EEG sensor.

In [12] the authors use an ultrasonic device directed to a person to read micro-Doppler signatures of actions by transmitting an ultrasonic wave and measuring the reflection. These signatures are used with a k-means classifier to classify a small number of activities with good accuracy. For activity recognition, inertial sensors can also provide detailed information [3].

The *sociometric badge* is a multi-sensor device to collect data during social interactions [29]. It can gather proximity data via sensing other badges, measure acceleration in 3D, and record speech. These badges were used to analyze dominance effects in group interactions in [24].

3.4 Ambient settings and immersive platforms

RFID tags attached to objects can reveal usage patterns very easily, and these have been used in ambient settings [57]. Similarly, location occupation information can be obtained with non-intrusive passive infrared sensors (PIR) from an indoor environment [58]. The data obtained with such sensors can be mined for patterns, or triggers can be implemented if certain behaviors are expected.

3.5 Virtual settings

Virtual behavior of people can be analyzed in similar ways to real behaviors. Here, more traditional sensors that measure physical phenomena are replaced by virtual sensors that provide data. Typical examples are social networks, from which interaction and activity patterns can be extracted [5], and mobile phones, which can reveal usage patterns and locations [13]. The existence of underlying social connection structures in most of these applications brings a wealth of additional information that can be used in prediction or profiling. Yet these media, unless enhanced specifically, have little to offer in terms of detailed face-to-face social interactions.

4 Applications

In this section we provide application examples from four domains, and discuss the mechanisms of inducing change, as well as the HBU technology used in the process.

4.1 Healthcare and wellbeing

HBU can provide self-monitoring applications with quantitative data, and play an important role for healthcare and wellbeing applications. For instance, the *Houston* mobile application encourages individuals to take more steps each day by providing self-monitoring and social data sharing over mobile phones [11]. For the proposed application, pedometers were used to determine activity levels. Similarly, Gasser et al. 2006 encourage eating more fruits and vegetables via self-monitoring, but the setting is much more difficult to automatize data collection for target attainment.

The behavior to be influenced sometimes cannot be accurately assessed by the subject, and a computer system can be better positioned to provide assessment. These applications illustrate how the domain extends beyond persuasion.

In [22], a wearable sensor system is described to help patients after a hip replacement operation. The doctor provides the system with thresholds and rules for admissible postures and movements, and the system monitors the patient at all times, to sound an alarm when dangerous behavior is engaged. In the IS-ACTIVE project[1], the aim is to develop a person-centric solution to induce activity in people with chronic conditions, like the chronic obstructive pulmonary disease (COPD). A typical problem with these patients is that the fear of damaging themselves (or in the case of COPD of having a breating problem) drives the patient to a mostly static lifestyle, which aggravates the condition. Realtime analysis allows self monitoring, whereby the patient can perform exercises while receiving feedback about how far they are to a critical overload condition. Alemdar and Ersoy provide an extensive survey of the usage of wireless sensor networks in health-care [1], and include applications like monitoring a patient for medication intake, status monitoring, activities of daily living and location tracking. Avci et al. survey the usage of inertial sensors for activity analysis in healthcare, sports and wellbeing applications [3].

4.2 Serious gaming

Serious gaming is an area where games are designed with the purpose of teaching, skill acquisition, training, attitude and behavioral change. Since games serve entertainment, the primary mediator of behavioral change is the entertainment feedback, but other motivational factors like challenge, fantasy, curiosity, control, as well as social factors are also considered [8, 37]. Bogost coined the term persuasive games to describe games designed to change behaviors and attitudes [7]. In the present volume, Rozendaal et al. describe the "Intelligent Play Environments" program, which deals with the design of playful interactive systems that stimulate physical and social activities [50]. We note here that only in rare cases is HBU integrated into gaming applications, primarily because the technology is deemed less than adequate. With new developments in sensors (for instance RGB-D cameras that facilitate real-time gesture recognition and portable EEG sets), the gaming industry sees more applications in this area [54].

4.3 Marketing

Marketing applications have been dominant particularly in virtual settings. Here, the aim is to influence buying behavior of as many people as possible. One way of achieving this is to rely on the way ideas are spread in social networks, and to seek to influence a proper subset of the population by analysing their buying behavior, letting social dynamics take care of the rest [26]. A very hot application area is **interactive marketing**, where HBU technology can be used to drive interaction. The interaction is typically an audio-visual experience, which is somehow related to the advertised product, and the viewers become a part of the whole setup. We give the example of the University of Amsterdam spinoff

[1] http://www.is-active.eu/

ThirdSight, which installed such a system on the biggest advertising screen in Amsterdam (on Rembrandtplein), where computer vision was used to allow people to interact and play with virtual balloons[1]. Another use of HBU in marketing is to determine location and head pose of a shop-viewer to measure presence and attention. Reitberger et al. describe a shop mannequin that turns toward and gazes at the customer, providing a more engaging interaction [49].

4.4 Energy saving and sustainability

In her keynote talk at HBU'11, Nuria Oliver discusses the emerging area of urban computing and smart cities in general and improving the quality of life of an urban environment by understanding the city dynamics through the data provided by ubiquitous technologies in particular [42]. This information can be used by city planners to improve infrastructure, as well as to create appropriate relief plans. The interest is also rising in systems that reduce energy consumption at home or work [23]. In [17], a system was proposed to augment thermostats by processing information from location-aware mobile phones. Even a simple context sensing approach can be useful for reducing individual energy costs.

5 Conclusions

HBU is our collective term for the toolbox of methods used in computer analysis of human behavior, and as we have shown, such analysis has many uses for persuasion, as well as for inducing behavior change beyond persuasion. Human behavior is complex; a certain behavior will be prompted by habits or intentions, modified based on skill, affect and attitude, influenced by physical and contextual conditions, and the results will be available to the computer via sensors, which capture a limited portion of reality with some noise. The models of HBU can thus be directed to make inferences about any of these influences on the outcome: What is the intention of the subject? Is the subject an expert? How does the subject feel? Does the subject have a positive attitude? What is the context of this behavior? We can certainly ask many more questions, and devise new ways of harnessing HBU for inducing behavior change.

Model-based approaches can go very deep in a particular domain. Starting from the seminal work of Schank and Abelson on scripts and plans [53], we have seen that by charting out detailed descriptions of the possibilities for actions and activities in a semantically limited domain (ordering food in a restaurant in the archetypical example) it is possible to associate meaning to sensed behavior. Yet, there are almost no limits to the domains of behavior, and one can imagine for the future vast repositories of behavior ontologies accessible over the Internet as a potential solution for substituting common knowledge. In recent years, we have witnessed the power of brute force computation in diverse domains. Also in HBU, researchers are building models sufficiently rich for particular application

[1] http://www.thirdsight.co/technologies/interactiveadvertising/

domains, which means that all relevant behaviors that can be conceived of as being salient within the context of the domain can be fruitfully distinguished. It is imperative to understand the capabilities and limits of existing HBU approaches to tailor them for practical solutions.

Amid all this scaling up of approaches to previously inconceivable computational resource expenditure, the data sources available for analysis are also vastly enriched. Beyond novel sensory modalities like RGB-D cameras and real-time data streaming smartphones, the social aspects of human behavior became the subject matter of computer analysis. Beyond doubt, this brings new challenges and new opportunities to the table.

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