

Dynamic Modeling of Human Behavior with AI

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ABSTRACT

The integration of artificial intelligence in human behavioral modeling has revolutionized how we analyze, predict, and understand human actions and decision-making. With the help of machine learning and Large language models, AI offers unparalleled capabilities to identify complex behavioral patterns and correlations across diverse domains such as marketing, healthcare, education, and public policy. By processing vast data sets in a relatively short time, it can analyse thousands of data points and accurately predict human behavior with the help of reinforcement learning making it better at every iteration. This article explores the potential of AI in behavior modeling. Applications, benefits and ethical dilemmas are presented.

Keywords: Human-Centric AI, Cognitive Behavioral Analysis, Human Behavior Modeling, Emotion Detection, Stress Detection, Deception Detection, Reinforcement Learning, Active Learning, Ethical AI, Human-AI

INTRODUCTION

Human Centric AI (HCAI) is expected to be a basic element in the autonomy of AI agents. Quite interestingly, AI agents will need to interpret human behavior in context to better interact with users, understand their actions, predict their choices, and ultimately juggle between actions performed directly by humans and those delegated to AI agents in autonomy. Therefore, it is essential to equip AI agents with practical models of human behavior. Utilizing models of human behavior and decision making has spanned decades across number of approaches and applications. Human behavior and reasoning enables complex behaviors and social structures. Consequently, these structures become multifaceted and grow significantly in complexity. Interestingly, humans are generally quite good at navigating this complex social structure. There are a multitude of attempts at explaining aspects of these capabilities, and this article discusses some of the more popular or persistent methods.

Cognitive behavioral analysis

Cognitive Behavioral Analysis is needed to understand the occurrences of such cognitive reactions. A review of cognitive behavioral analysis of psychological problems like negative thoughts, lies, stress, and abnormal behaviour is discussed. It is classified in three types:

1. Lie/deception detection
2. Stress/emotion detection
3. Abnormal Behavior detection

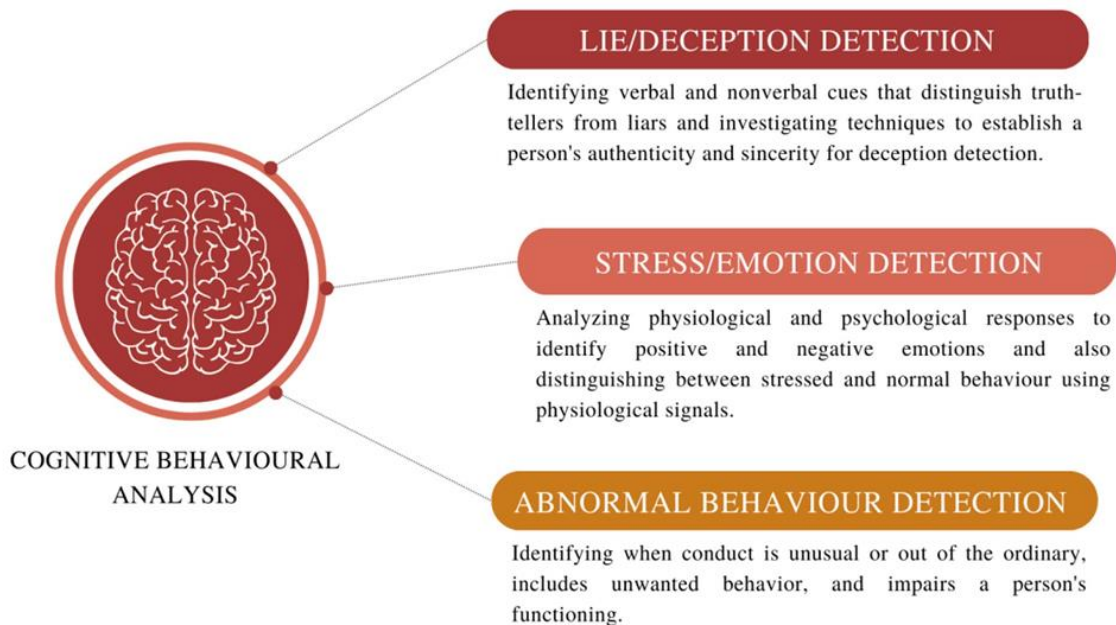


Figure 1. Types of Cognitive Behavioral analysis.

Lie/Deception Detection

The aim of the lie detection test is to identify verbal and nonverbal cues that distinguish truth-tellers from liars. Detecting the difference between liars and truth-tellers has been a topic of interest throughout history. Questioning strategies are mainly used in lie or deception detection to determine true and false responses. However, human beings have a tendency to observe and understand visual cues. Hence, the most transparent approach in every study was to record videos or take pictures.

Stress/Emotion Detection

Emotion is a mental and physiological process triggered by the awareness or unawareness of an object or situation. It is causally linked to mood, temperament, character, inclination, and desire. Emotions play an important part in human communication and can be represented verbally through emotional language or nonverbally through gestures, facial expressions, and voice. Emotion Detection analyses physiological and psychological responses to identify positive and negative emotions. Negative emotions could also lead us to stress.

Stress is an intensified psycho-physiological state of the body that develops in reaction to a demanding situation or challenging occurrence. Stressors are the factors in the environment that cause stress. Prolonged exposure to multiple stressors can negatively impact a person's mental and physical health which can lead to chronic health issues. It is crucial to detect stress-related problems early on to prevent them, and this can only be accomplished through continuous monitoring of stress levels. The feeling of stress is frequently accompanied by visual clue. Self-directed behaviours such as lip-biting, face-touching, and scratching are among them.

Malicious Intent detection

Having or displaying the desire to harm someone is known as having malicious intent, which can be given to, marked by, or resulting from malice. With the sudden rise in social media, micro-blogging sites like Twitter have already started detecting, censoring, and blocking people with "hateful" behaviour.

Malicious intents can be detected through speech, video, and audio. It can also be detected by using physiological sensors, such as functional magnetic resonance imaging (fMRI) or electroencephalography (EEG), to identify patterns of brain activity that may be active indicating malicious intent. However, this technology is still developing and needs to be more reliable to identify malicious intent in real-world settings. Additionally, interpreting brain activity patterns is a complex task requiring neuroscience and machine learning expertise.



Figure 2. Human Behavior representation.

Agent Based Modeling

In ABM, human behavior models are often defined and then studied in an environment over a simulated timeline. The agents follow the defined patterns of behavior and the resulting global patterns can be analyzed. For instance, population segregation based on demographic preferences regarding neighbors can be modeled by defining a diversity preference and modeling the movement of agents in an environment. Populations of humans can also be modeled with other techniques designed to model the interdependence

of the agents. The interactions can be modeled mathematically with humans represented as nodes in a network, particles environment, or more.

Reinforcement Learning

RL is a method by which situations are mapped to actions to maximize a reward signal. The maximization is performed by the learning agent through exploration of an environment and the possible actions. This exploration generates a feedback signal via rewards that the agent uses to learn the behaviors resulting in the most desirable feedback. The feedback received is provided immediately or can be a result of a sequence of actions. For example, an agent could receive a reward for each step they make in an environment or simply a single reward at the end of a training session that corresponds to the outcome. The different parameters of the problems lead to numerous techniques for learning optimal behavior policies.

Active Learning

AL is intended as an AI paradigm by which the learner is able to query an oracle regarding unlabeled data. The goal is to enable a more efficient usage of data sets by allowing the learner to identify which items should be prioritized based on their experience in the simulation. This is described as a characteristic similar to the concept of curiosity in humans, since AL demonstrates a motivation to inspect items with less experience or certainty. Note that this relates to how the system decides what it wants to learn more about, not a true reproduction of human cognition. However, it has been argued that humans must regulate their priorities regarding curiosity to know when and what to learn. When prompted, the oracle can then provide labels for the queried samples, reducing the need to label larger sized datasets prior to the start of training.

Literature Review

Olivia Nocentini (2019) The collaboration between humans and robots is becoming increasingly significant in our society. As a result, there's a growing interest in creating models that enhance and deepen human-robot interactions. A key challenge for Human-Robot Interaction (HRI) is to equip the machines to understand human emotions and to be more empathic in behavior. This work has done a study on this area. Study has found that there are three key components of HRI;

- (a) developing adaptive behavioral models,
- (b) cognitive architecture design and
- (c) training of empathetic behavior.

Literature survey of fifty-six articles was done for detailed analysis.

Priya Bhatt (2023) has done research on human behavioral analysis and trained a computer using machine learning. Cognitive behavior is defined as the ability to perceive, process, interpret and remember information while making decisions. The various emotions trained by machine learning were joy, grief and anger. To manage emotions one has to distinguish between thoughts and feelings. After the model was trained on emotions, the focus shifted towards the perception and identification of things like intent, emotions, stress etc. Those things are quite difficult for any person to perceive but with enough experience, it can be done. To train AI models to perceive others' emotions requires a lot of meta data, and the authors have trained the models of thousands of data points. The current research on cognitive behavioural science training is reviewed and challenges have been identified and future scope has been proposed.

Zakaria Aoujil (2023) has reviewed research on the use of AI models which are trained on human behaviors. The study reveals that there has been an increase in publications regarding the training of AI models over the past decade. Many authors have focused on customer behavior tracking, decision making uncertainty, macroeconomics, behavioral game theory, behavioral finance, nudging and prospect theory. The studies indicate that there is a need for greater interdisciplinary collaboration among scientists of different fields, this would truly push the limits of AI research and help improve the economy.

Abhishek Aggarwal (2023) has studied the use of AI in promoting health behavioral changes in people. Research articles from 1980 have been reviewed for this study. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) was performed to analyse the research papers. A survey was conducted on fifteen participants. Results showed that AI had good performance in promoting a healthy lifestyle. Four participants stopped smoking altogether thanks to AI intervention. Behavior change theories and strategies from top psychologists was encoded in AI to help the participants. Goal setting, monitoring, real time feedback from AI was implemented. User behavior was collected from the participants to identify ways of providing personalized solutions. The applicability of AI to be used on social media platforms was analyzed. Participants reported that AI was non judgemental which helped them to converse without worrying about the outcome.

Zhihan Lv (2023) discusses the issue of the social intelligent ecosystem (C&P-SIE). This is a system of social media spaces in which the user information is publicly available. This study focuses on physical social intelligence. Discussion on behavior modelling, learning and adaptation of C&P - SIE is shown. The application of C&P-SIE on transportation, healthcare, public service, economy and social networking is discussed. The overall motive of using AI on those systems is to improve them and provide real time solutions of various problems faced in those systems since all those are man made.

Xinru Wang (2022) has focused the assistance of AI in the decision making process. The human decision cognitive process is classified in two components: (a) the utility component and (b) the selection component. A development of an AI model incorporating those components is the objective of this study. For example, AI can advise an investor regarding buy or sell situations in the trading market. Talking about AI application in medicine and health, AI models can detect diabetes in patients through retina scans, this obviously has to be a proven method used by scientists and the literature should be published in top journals. For the AI to reach its full potential in depth understanding of human decision making process, intentions and emotions is necessary.

Andrew Fuchs (2023) have studied the modeling of human reasoning with the help of AI. Topics such as Game theory, theory of mind and machine learning are integrated into the models. In addition, next-generation entrepreneurs and autonomous, adaptive systems will largely include AI agents and humans working together as teams. To make this possible, autonomous agents will be required to embed practical models of human behavior, allowing them not only to replicate human models as a technique to “learn” but also to understand the actions of users and anticipate their behavior, so as to truly operate hand to hand with them. The main objective of this article is to provide systematic review of important approaches in two areas dealing with quantitative models of human behaviors. Specifically, the authors have focused on (i) techniques that learn a model or policy of behavior through exploration and feedback, such as Reinforcement Learning, and (ii) directly model mechanisms of human reasoning, such as beliefs and bias, without necessarily learning via trial and error.

Conclusion

Artificial intelligence has been a revolution in the field of human behavioral modeling by offering unprecedented tools for analyzing, predicting, and influencing human actions. Its ability to process vast amounts of data with speed and precision has enabled researchers and organizations to gain deeper insights into complex behavioral patterns, ranging from consumer preferences to psychological traits. AI models, powered by machine learning and natural language processing, can identify subtle patterns and correlations that were previously inaccessible through traditional methods. This has immense implications for industries such as marketing, healthcare, education, and public policy, where understanding human behavior is of utmost importance in achieving the required objective.

By integrating real-time data from sources such as social media, wearable devices, and IoT systems, it allows for continuous updates to models, ensuring they remain relevant and accurate in changing environments. However, use of AI in behavioral modeling also raises ethical concerns, like individual privacy, and the potential for misuse in surveillance systems. It is therefore required to establish robust laws to make sure that misuse of AI does not happen.

In conclusion, it can be seen that AI has a lot of potential which has shown that it can detect cognitive behavior responses. However its implementation should be within the law of the land. AI developers should use it responsibly.

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