Exploring the Dynamics of Cognitive AI

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Abstract

This paper provides an overview of cognitive Artificial I4ntelligence (AI), a field that enriches machines with human-like cognition. It explores the distinctions between cognitive AI, conventional AI, and Artificial General Intelligence (AGI). The paper delves into cognitive theories such as Personality Systems Interaction (PSI) theory, Maslow's hierarchy of needs, Kuhl's theory of motivation and personality, and Michael Bratman's theory of intentions, highlighting their relevance to AI and human behavior. The study also covers essential AI techniques, including Artificial Neural Networks (ANN), Hidden Markov Models (HMM), and metaheuristic algorithms, discussing their applications across various industries. Ethical aspects of bias in Machine Learning (ML) are addressed, emphasizing on data pre-processing. The paper concludes with a glimpse into the future prospects of cognitive AI, discussing its potential in healthcare, finance, customer service, and more. This overview encapsulates the paper's exploration of cognitive AI and its implications for bridging the gap between human and artificial intelligence.

Keywords: Artificial Intelligence, ANN, Cognition, HMM, Metaheuristic

Introduction

In the vast expanse of technological innovation, Artificial Intelligence (AI) has developed as a beacon of human ingenuity, reshaping our world in ways that once resided solely within the realm of science fiction. Today, AI is omnipresent, from our smartphones and self-driving cars to healthcare systems and online shopping recommendations. At its core, AI leverages advanced algorithms and data-driven approaches to enable machines to analyze, learn, adapt, and make decisions, often with a degree of autonomy and efficiency. The inception of AI can be traced back to 1956, where McCarthy and Minsky, along with their team, convened to explore the possibility of creating machines with human-like intelligence. Over time, AI has evolved from symbolic AI to connectionism and finally to the deep learning era we find ourselves in today.

In recent years, the intricate relationship between consciousness, the mind, and information has been the subject of intense scrutiny, with various models proposed, some of which are rooted in the enigmatic domain of quantum phenomena. These models have led to advanced insights, addressing significant questions ranging from the nature of consciousness to the mind-body connection and the interplay between predisposition and upbringing.

They have also shed light on areas as diverse as music-based therapy for neuro-rehabilitation, attitude assessment with wide-ranging applications, health equilibrium, mental aggressiveness, religious phenomena, and extra-sensory events. Over centuries, humanity has grappled with profound questions regarding the universe, life, and consciousness. In our modern era, replete with information-driven communication, these questions remain largely unanswered when approached within the confines of individual disciplines such as philosophy, neurosciences, and biology without the integration of information science. The Cognitive-Sentient Exploration of Reality (CSER) emerges as an innovative paradigm, uniting introspection and motivation at the delicate junction of certainty and uncertainty. With its roots in ancient civilizations, this convergence of intellectual currents has shaped traditional philosophy and continues to influence scientific exploration, education, medicine, and creative domains [1].

The introduction of cognitive AI marked the shift from AI as a conceptual framework to the fusion of machine learning with human-like cognitive abilities. It thus seeks to endow machines with the ability to comprehend, reason, and make context-driven decisions akin to human cognition.

Difference between AI, Cognitive AI and AGI

To appreciate its unique place in the AI spectrum, it's essential to delineate Cognitive AI from both conventional AI and AGI (Artificial General Intelligence). Conventional AI is a broad category encompassing systems designed for specific tasks bounded by rules. In contrast, AGI embodies the aspiration of creating machines that possess human-like general intelligence, capable of flexibly performing a wide range of tasks such as diagnosis, and multilingual translation. Yet, it's crucial to acknowledge that AGI remains an ongoing

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quest, with early-stage developments. Cognitive AI, situated as a subdomain within the AI landscape, occupies a middle ground. What defines cognitive AI are its cognitive abilities, which include natural language understanding, context comprehension, and the capacity to draw inferences, much like virtual assistants Siri or Alexa. In essence, cognitive AI functions as a vital bridge between the specialized proficiency of conventional AI and the comprehensive potential of AGI, delivering a unique amalgamation of cognitive prowess within the AI domain [2].

Cognitive Theories Exploring Human Behaviour

As we navigate the intricate realm of cognitive artificial intelligence, we find ourselves traversing a diverse and multifaceted landscape of theories that unveil the enigmatic intricacies of human motivation and behavior. In this academic discourse, we undertake a thorough investigation of four distinct theories. Each theory provides a unique perspective for examining the intricate workings of the human mind and their profound implications for the realm of artificial intelligence. These theories provide us with profound insight into the intricate interplay of computational and psychological mechanisms that govern our decision-making processes, impel our actions, and fundamentally shape our individual and collective conduct.

a. PSI (Personality Systems Interaction) Theory

This theory, rooted in the intricate landscape of cognitive artificial intelligence, unfolds as a comprehensive model elucidating the intricacies of motivation, decision-making, and cognitive-social behavior in both human and artificial systems. PSI theory, integrated into the MicroPsi architecture, is a comprehensive model for understanding human motivation and behavior. It explores the hierarchy of human motivation, from basic needs to complex desires, guiding human actions. Reinforcement learning is central, shaping behavior through feedback. Adaptive decision-making is a key aspect, allowing responses to changing situations and varying needs. It extends to social behavior, considering personal and social motivations. Implemented as a computational model, Psi theory enables AI systems to mimic human decision-making, enhancing their responsiveness to dynamic environments [3-5].

b. Maslow's Hierarchy of Needs

Maslow's Hierarchy of Needs, developed in 1943, is a foundational psychological theory. It arranges human needs into a pyramid structure with five levels, from basic survival needs like air and food at the bottom to the pursuit of personal growth and self-actualization at the top. While individuals typically prioritize lower-level needs first, it's essential to recognize that cultural and individual differences can influence this hierarchy. Nonetheless, the theory continues to be a fundamental concept in psychology, offering insights into human motivation and well-being [6].

c. Kuhl's Theory of Motivation and Personality

Kuhl's Theory of Motivation and Personality, developed by psychologist Joachim Kuhl, explores the interplay of different psychological systems and their effects on motivation and personality. The theory introduces two distinct processing modes: "harmonious" and "contradictory." In the harmonious mode, individuals experience coherence, flexible thinking, and positive emotions, while the contradictory mode is marked by inner conflicts, rigidity, and negative emotions. Adaptive functioning involves switching between these modes, using each as needed. Personality development is linked to this adaptability, with adaptive individuals having more balanced personalities. Emotional regulation plays a role, with positive emotions tied to the harmonious mode and negative emotions to the contradictory mode. Kuhl's theory emphasizes cognitive flexibility and its role in personal growth and well-being, finding applications in psychology, counseling, and self-development [7].

d. Michael Bratman's Theory of Intentions

Michael Bratman's Theory of Intentions, Plans, and Practical Reason provides a comprehensive framework for understanding human intentional action, planning, and practical reasoning. It distinguishes various levels of intention, with "settled" intentions representing firm commitments to future actions. Intentions are closely tied to plans, which outline the steps required to achieve goals. Practical reasoning is the cognitive process through which individuals make choices based on their intentions and beliefs about rationality and desirability. The theory emphasizes means-end rationality, self-governance, and the importance of self-knowledge and self-control in goal pursuit. Bratman's theory sheds light on how humans engage in purposeful, goal-oriented behavior and is applicable to philosophy, psychology, ethics, and decision theory, offering insights into human agency and rationality [8-9].

AI Techniques for Cognitive Intelligence

a Artificial Neural Network

In 1943, the inaugural ANN was introduced by the collaborative efforts of neurophysiologist McCulloch and logician Pitts, marking the inception of a computational model inspired by the intricacies of the human brain. These artificial neural networks are intricately constructed systems composed of interconnected artificial neurons, each possessing adjustable parameters designed to generate predetermined outcomes.

Diverse ANNs exist, differentiated by the configurations of network and methodologies of training, sharing a fundamental architecture of neurons that aggregate inputs to produce singular outputs. Within the domain of cognitive radios (CRs), several prominent ANN categories come to the forefront [10]:

- Multi-layer Linear Perceptron Networks (MLPN): MLPNs feature layers of neurons, with each layer constituting previous layer's output's linear combination. The training of MLPNs is facilitated by diverse methodologies, including backpropagation (BP) and genetic algorithms (GAs), selected based on network dimensions and specific application requirements. Hybrid strategies combining GA pre-training with BP refinement are also a prevalent approach [10].
- Nonlinear Perceptron Networks (NPN): NPNs introduce a layer of nonlinearity into the network, enabling tailored adaptation to match specific sample datasets. The inherent flexibility of NPNs is balanced by the need for congruence between network configurations and the data they represent. Training these networks through BP may involve protracted convergence times [10].
- Radial Basis Function Networks (RBFN): RBFNs incorporate a radial nonlinear function, frequently Gaussian, within their hidden layer to establish a distance-based criterion relative to a central point. This construction strategy mitigates the common issue of networks converging into local minima. Training RBFNs typically employs gradient descent as the preferred method [10].

The application of ANNs to CRs capitalizes on their intrinsic adaptability, permitting dynamic "learning" of system patterns, attributes, and complexities. This adaptability extends to the handling of intricate, nonlinear, and multifaceted attributes, often requiring only minimal examples to navigate. As a result, ANNs prove invaluable not only in stimulus recognition and classification but also in guiding and enhancing the adaptation process [11-12].

b. The Hidden Markov Model (HMM)

Introduced in 1960s, the HMM stands as a mathematically elegant and tractable statistical framework, uniquely equipped to model and analyze dynamic behaviors within complex, stochastic phenomena. HMMs find their primary application in the representation of systems characterized as Markov processes. Such systems encompass both observable and unobservable states, where sequences of observation symbols emerge through state transitions, with the concealed states. These state transitions are capable of generating sequences of observation symbols, which may either be discrete or continuous [13].

A concise representation of an HMM is encapsulated by the notation shown in eq. 1:

$$\lambda = (A, B, \pi(1)) \tag{1}$$

incorporating the state transition probability matrix A, which possesses a dimension of $N \times N$, the observation symbol probability matrix B with dimensions of $K \times N$, and the initial state probability vector $\pi(1)$ with a dimension of $N \times 1$. N signifies the number of states within the model, whereas K denotes the count of distinct observation symbols linked to each state [13].

Within the realm of practical applications, HMMs are associated with three fundamental problems:

- Evaluation or Recognition Problem: This problem entails the computation of the probability associated with a specific observation sequence when provided with the model parameters represented by λ. The forward–backward algorithm stands as the principal method for resolving this challenge [13].
- Decoding Problem: When armed with both model parameters λ and an observed sequence, the principal objective becomes the identification of the sequence of hidden states that best elucidates the observation sequence. In this context, the Viterbi algorithm emerges as the preferred solution [13].
- Training or Learning Problem: The "Training or Learning Problem" in HMMs revolves around estimating the most probable set of state transitions and observation symbol probabilities when presented with an observation sequence. This problem is a subset of the broader expectation-maximization paradigm and is typically resolved using the Baum-Welch algorithm. In the context of CRs, the application of HMMs involves tailoring models to clarify and categorize observed symbols or patterns. These models are invaluable for identifying sequences with similar patterns, enhancing the cognitive engine's ability to recognize, classify, and become more aware of incoming stimuli. Furthermore, HMMs' capacity to replicate training sequences empowers predictive applications and facilitates the creation of new models [13].

Utilization of HMM:

- The application of HMMs involves the development of custom-tailored models designed to elucidate and categorize observed symbols or patterns. These models serve as powerful tools for discerning sequences characterized by analogous patterns, driven by the selection of the model best-suited to explain the observed sequences. Consequently, HMMs assume a significant role within the cognitive engine's observation process, contributing to the recognition, classification, and heightened awareness of received stimuli. Furthermore, HMMs' intrinsic capability to replicate training sequences empowers predictive applications, while their potential for facilitating learning is exemplified through the creation of new models [13].

c. Metaheuristic Algorithms

Table 1: Characteristics of Metaheuristic Algorithms

Decision Process	Key Benefits	Drawbacks
Classical Techniques	Offers globally optimal answers to a range of convex optimization issues: Analysis of convergence qualities is thorough [15].	Could produce less-than-ideal (undesirable) answers for dysfunctional functions; In addition to being computationally demanding, branch-and-bound, clustering, and multi-start approaches that improve performance require access to global information.
Genetic Algorithms	Well-investigated for wireless applications [16].	Convergence has not been fully investigated: Efficiency depends on proper parameter selection.
Simulated Annealing	Asymptotically converges to a globally optimal solution with probability 1; Easy to implement [17].	Convergence rate may be slow; Only converges to a global optimal as time approaches infinity for a finite search space.
Tabu Search	Simple to implement [18].	Effectiveness depends on choosing the right parameters
Ant Colony Optimization	Able to quickly adjust to changes in reality [19-20].	Not as effective as simulated annealing in local search.

Explicit relationships between the parameters of an AI system and its preferred metrics for performance evaluation are typically unavailable. Consequently, conventional search algorithms based on mathematical relations are ill-suited for identifying optimal parameters that align with specific performance metrics. Instead, the utilization of metaheuristic algorithms [14] becomes essential when tackling computationally challenging problems, enabling a comprehensive exploration of the solution space and the acquisition of the necessary relationships. While the term "metaheuristic" likely first appeared in 1986, its roots trace back to earlier research on stochastic optimization methods during the 1950s [15]. This discourse introduces a curated selection of metaheuristic algorithms for consideration, as presented in table 1.

Rule-Based Systems (RBS)

In a RBS, rules are derived from specific application areas, facilitating decision-making. This approach encodes human expert knowledge into automated systems. RBS, with its foundation dating back to DENDRAL in 1964, comprises essential components: the rule base and the inference engine (IE). The IE operates through forward chaining or backward chaining [21-22].

In the context of CRs, RBS offers simplicity. It rapidly deduces actions for input, though it relies on a well-defined rule base. Challenges arise when a domain is not entirely understood. Strategies to mitigate this include assigning certainty values to rules, employing statistical tools like Bayesian analysis, or combining RBS with a case-based system. Notably, RBR-CEs have been designed for CR, providing effective performance with reduced complexity. Deriving rule databases systematically through automated experiments is another approach, allowing optimal configurations for specific conditions and requirements [23-25].

Case-Based System (CBS)

The CBS in AI has its roots in Schank's dynamic memory models from the 1980s. It utilizes prior similar cases to guide problem-solving and derive solutions. CBS involves selecting the most relevant cases, narrowing them down to a single case, and adapting it to the current context, often seen as an optimization challenge. Initial case retrieval, based on similarity, jumpstarts the optimization process, reducing the computational effort and time needed for parameter optimization. CBS is characterized by problem-solving in partially understood domains, providing unique explanations, and mimicking human reasoning processes. However, CBS performance relies on the correctness of prior case solutions, making it susceptible to propagated mistakes from inaccuracies in past cases. In complex domains, creating and examining a large database can be laborious. In such cases, incorporation of different techniques, like rule-based systems (RBS), can enhance performance and expedite the case database [26].

In a CR context, CBS helps the system determine actions based on the current environment and radio objectives, using cases in a database. CBS learns new cases for novel situations, updates the case database, and generates new actions. Recent advances in CBR for CR design include Reed et al.'s CBR-based Cognitive Engine (CBR-CE) for IEEE 802.22 WRAN applications, Khedr and Shatila's CE using CBR and fuzzy logic for WiMAX channel type identification, and Le et al.'s CE architecture incorporating CBR [27-28].

A comparison between the different cognitive AI techniques discussed is presented in table 2.

Table 2: Comparison between different Cognitive AI Techniques

Algorithm	Strengths	Limitations	Options
Artificial neural network	Able to explain a wide range of tasks ANN is conceptually simple to scale. Excellent for categorization. Able to spot novel patterns.	Depending on the size of the network, training could be slow. Over training is possible. There is no need to connect application to theory.	Able to employ different learning strategies throughout the training stage (i.e. GA) Can be combined with RBS.
Metaheuristic algorithms	Excellent for understanding relationships between parameter values and parameter optimization. Able to employ different learning strategies throughout the training stage (i.e. GA)	It is challenging to design a rule space when learning or optimisation is not limited by parameter values.	Capable of being combined with RBS. The process of searching might also benefit from learning.
Hidden Markov model	Able to simulate complex statistical procedures. Suitable for categorization. Simple to scale.	Requires good training sequence. Computationally complex	CBS and RBS can assist HMM in determining the observation period for a particular application and overcoming challenges with novel conditions by drawing on prior knowledge.
Rule-based system	Simple implementation. Capacity to deal with unforeseen circumstances. Capacity to formulate rules with just relevant features included.	Tedious rule derivation process. Perfect domain knowledge is necessary, but it is not always available.	Can be used in conjunction with OBS and CBS to handle unknown domains more effectively.
Case-based system	Similar to how humans think. Capable of operating in a complex, high-variability environment. Enables quick knowledge acquisition and learning even in the lack of domain expertise.	Depends only on prior cases. Large case memory is necessary. May contain unrelated motifs.	Can be used in conjunction with RBS and OBS to create a more capable system for solving problems that isn't just dependent on experience.

Ethical Biases of Cognitive AI

Ethical concerns related to biases within machine learning systems have garnered significant attention in recent times. The core challenge underlying this issue is the presence of biases within the datasets used to train these systems, leading to algorithmic discrimination and the production of unfair or skewed decision-making processes. Often, this bias can be traced back to historical inequities embedded in the training data.

In response to this concern, substantial efforts have been directed at mitigating algorithmic discrimination, broadly classified into two categories: in-processing techniques and post-processing techniques. In-processing techniques involve the modification of learning algorithms during training to eliminate discrimination, whereas post-processing techniques aim to correct the outcomes of pre-trained classifiers to achieve fairness.

Nonetheless, as this discourse highlights, the crux of (un) ethical machine behavior is fundamentally rooted in the initial selection of data features for machine learning system training. The choice of what data and features are included significantly shapes the ethical behavior of the system. This text advocates that pre-processing techniques, involving the careful exclusion of undesirable inputs from the training dataset, are an underemphasized aspect of ethical machine learning.

Furthermore, it subtly suggests that the scope should extend beyond the mere avoidance of unfairness associated with protected attributes such as gender, age, or ethnicity. Instead, it emphasizes a comprehensive approach to selecting and filtering data inputs to ensure ethical behavior from the outset. This approach aims to prevent biases and discrimination at their source, rather than merely addressing their consequences in the outputs of machine learning models [29].

Conclusion and Future Scope

In the ever-evolving landscape of Artificial Intelligence, Cognitive AI emerges as a pivotal intersection between human-like cognition and machine capabilities, offering a compelling vision for the future of AI. This synthesis of advanced algorithms and cognitive abilities propels AI into a realm where machines, akin to humans, can understand context, reason, and make informed decisions.

Our profound exploration of this transformative field has unveiled a plethora of cognitive theories and AI techniques that not only illuminate the intricate workings of the human mind but also hold the potential to reshape the technological landscape.

Cognitive AI, situated at the crossroads of psychology and computer science, reflects a future where AI systems are not mere tools but cognitive companions, capable of understanding human emotions, motivations, and intentions. As this field matures, we anticipate an era where Cognitive AI will augment human decision-making, offering valuable insights and support in fields as diverse as healthcare, education, and customer service. It holds the promise of enhancing our daily lives, from personalized healthcare recommendations to advanced educational tools.

However, alongside these transformative prospects, it's imperative to address the pressing ethical concern of bias. Bias in machine learning systems is a critical issue, and this calls for stringent measures in data pre-processing and algorithm design. Ensuring fairness, not just in protected attributes but in a comprehensive selection and filtration of data inputs, will be essential to achieving ethically sound Cognitive AI systems.

As we gaze into the future, Cognitive AI stands as a monumental milestone, bridging the chasm between conventional AI and the ambitious dream of Artificial General Intelligence. It aligns with human cognition and extends the frontiers of machine capabilities, promising a future where AI doesn't merely perform tasks but comprehends and decides, enriching human lives and industries across the board.

In the coming years, we can anticipate the proliferation of Cognitive AI across various sectors, including healthcare, finance, and autonomous systems. Healthcare providers will harness Cognitive AI to improve diagnostics, while financial institutions will employ it for risk assessment and fraud detection. Autonomous systems, from self-driving cars to smart homes, will rely on Cognitive AI for enhanced decision-making and situational awareness.

In conclusion, the future of Cognitive AI is marked by a profound transformation in human-machine interaction, where AI systems are not just tools but partners in decision-making, fostering a deeper understanding of human behavior and motivations. The evolution of Cognitive AI holds the promise of a more ethically aware, intelligent, and integrated technological future.

References

1. Gaiseanu, F. (2019). Language patterns and cognitive-sentient reality: Certainty/uncertainty in cognitive-sentient exploration of reality. In *Media models to foster collective human coherence in the PSYCHecology* (pp. 49-72). IGI Global.
2. Cichocki, A., & Kuleshov, A. P. (2021). Future trends for human-ai collaboration: A comprehensive taxonomy of AI/AGI Using Multiple Intelligences and Learning Styles. *Computational Intelligence and Neuroscience, 2021,* 1-21.
3. Dörner, D.: Bauplan für eine Seele. Reinbeck (1999).
4. The Dörner, D., Bartl, C., Detje, F., Gerdes, J., Halcour, D.: Die Mechanik des Seelenwagens. Handlungsregulation. Verlag Hans Huber, Bern (2002)
5. Bach, J. (2009). PSI–An architecture of motivated cognition. Oxford University Press, *Oxford*.
6. Maslow, A. H., Frager, R., Fadiman, J., McReynolds, C., & Cox, R. (1987). Motivation and personality (3rd). *New York*.
7. Kuhl, J. (2001). *Motivation und persönlichkeit: Interaktionen psychischer systeme.* Hogrefe.
8. Bach, J. (2017, September). Motivated, emotional agents in the MicroPsi Framework. In *Proceedings of the European Cognitive Science Conference 2007*. Taylor & Francis.
9. Bratman, M. (1987). Intention, plans, and practical reason, Harvard Un. *Cambridge, MA*.
10. Haykin, S. (1998). *Neural networks: a comprehensive foundation.* Prentice Hall PTR.
11. Fehske, A., Gaeddert, J., & Reed, J. H. (2005, November). A new approach to signal classification using spectral correlation and neural networks. In *First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005*. (pp. 144-150). IEEE.
12. Cattoni, A. F., Ottonello, M., Raffetto, M., & Regazzoni, C. S. (2007, August). Neural networks mode classification based on frequency distribution features. *In 2007 2nd International Conference on Cognitive Radio Oriented Wireless Networks and Communications* (pp. 251-257). IEEE.
13. Rabiner, L. R. (1989). A tutorial on hidden Markov models and selected applications in speech recognition. *Proceedings of the IEEE, 77*(2), 257-286.
14. Blum, C., & Roli, A. (2003). Metaheuristics in combinatorial optimization: Overview and conceptual comparison. *ACM computing surveys (CSUR), 35*(3), 268-308.
15. Glover, F. (1986). Future paths for integer programming and links to artificial intelligence. *Computers & operations research, 13*(5), 533-549.
16. Robbins, H., & Monro, S. (1951). A stochastic approximation method. *The annals of mathematical statistics*, 400-407.

17. DE, G. (1989). Genetic algorithms in search. *Optimization, and Machine Learning, Addison Wesley.*
18. Kirkpatrick, S., Gelatt Jr, C. D., & Vecchi, M. P. (1983). Optimization by simulated annealing. *Science, 220*(4598), 671-680.
19. Glover, F. W. and Laguna, M. Tabu Search. Boston, MA: Kluwer
20. Dorigo, M., & Blum, C. (2005). Ant colony optimization theory: A survey. *Theoretical computer science, 344*(2-3), 243-278.
21. J. Paine, Expert systems. [Online]. Available: http://www.j-paine.org/students/lectures/lect3/lect3.html
22. J. H. Reed et al., "Development of a cognitive engine and analysis of WRAN cognitive radio algorithms—Phase II," Wireless @ Virginia Tech, Virginia Polytech. Inst. State Univ., Blacksburg, VA
23. Zhao, Y., Gaeddert, J., Morales, L., Bae, K., Um, J. S., & Reed, J. H. (2007, August). Development of radio environment map enabled case-and knowledge-based learning algorithms for IEEE 802.22 WRAN cognitive engines. In *2007 2nd International Conference on Cognitive Radio Oriented Wireless Networks and Communications* (pp. 44-49). IEEE.
24. Clancy, C., Hecker, J., Stuntebeck, E., & O'Shea, T. (2007). Applications of machine learning to cognitive radio networks. *IEEE Wireless Communications, 14*(4), 47-52.
25. Weingart, T., Sicker, D. C., & Grunwald, D. (2007). A statistical method for reconfiguration of cognitive radios. *IEEE Wireless Communications, 14*(4), 34-40.
26. Kolodner, J. L., & Leake, D. (1996). A tutorial introduction to case-based reasoning. Cambridge, MA: MIT Press.
27. J. H. Reed et al., "Development of a cognitive engine and analysis of WRAN cognitive radio algorithms—Phase III," Wireless @Virginia Tech, Virginia Polytech. Inst. State Univ., Blacksburg, VA.
28. He, A., Gaeddert, J., Bae, K. K., Newman, T. R., Reed, J. H., Morales, L., & Park, C. H. (2009). Development of a case-based reasoning cognitive engine for ieee 802.22 wran applications. *ACM SIGMOBILE Mobile Computing and Communications Review, 13*(2), 37-48.
29. Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016). Machine bias. *ProPublica,* May 23, 2016.