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Bounded Rationality in Artificial Intelligence to Sensing

Sagar Choudhary[1], Dr. Sunil Damodhar Rathod[2]

[1]Research Scholar, Sunrise University, Alwar

[2]Sunrise University, Alwar

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Corresponding author: Sagar Choudhary

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Abstract:

The field of artificial intelligence (AI) has made significant strides in mimicking human cognitive processes, yet the concept of bounded rationality introduces a realistic lens through which AI systems approach decision-making, especially in the realm of sensing. Bounded rationality acknowledges the inherent limitations faced by AI systems in accessing complete information, allocating resources, and processing data in real-time. This abstract explores the implications of bounded rationality on AI systems engaged in sensing tasks within dynamic environments. In sensing applications, AI systems rely on various sensors to collect data from their surroundings. However, these systems often operate under constraints, such as limited computational resources, energy availability, and time pressure. Bounded rationality prompts a shift in perspective, emphasizing the need for adaptive and flexible decision-making processes that can effectively navigate uncertainties. The challenges posed by bounded rationality underscore the importance of developing algorithms that strike a balance between accuracy and computational efficiency. As AI continues to be integrated into various applications, understanding and addressing these challenges will be critical for the successful deployment of intelligent systems in real-world, dynamic environments. In conclusion, this abstract provides an overview of the impact of bounded rationality on AI systems engaged in sensing tasks. By recognizing and embracing the constraints inherent in decision-making processes, researchers and developers can pave the way for more realistic, efficient, and adaptable AI systems that navigate the complexities of dynamic environments.

Keywords: Artificial, Intelligence, Rationality, Bounded, Rationality, Decision-making, Sensing.

Introduction

Bounded rationality is a concept that originated in the field of behavioral economics and was later applied to artificial intelligence (AI). It suggests that decision-makers, including both humans and AI systems, have limitations in their ability to make fully rational decisions due to constraints such as time, information, and cognitive capacity. In the context of AI, bounded rationality plays a crucial role in understanding how systems perceive and respond to their environment, a concept that is particularly relevant to sensing.

Sensing, in the realm of AI, refers to the process by which machines collect data from their surroundings using various sensors and then interpret and analyze this information to make informed decisions. Bounded rationality in the context of sensing acknowledges that AI systems may not have access to complete information about their environment, and they may need to operate under resource constraints.

Here are key points to consider when discussing bounded rationality in the context of sensing in artificial intelligence:

Limited Information: AI systems often have access to only a subset of the available information in their environment. This limited information may be a result of sensor capabilities, environmental conditions, or data processing constraints. Bounded rationality recognizes that decisions must be made based on this incomplete information.

Resource Constraints: Sensing in AI is resource-intensive, requiring computational power, energy, and memory. Bounded rationality acknowledges that AI systems may need to make trade-offs in terms of resource allocation, leading to decisions that are not optimal but are practical given the limitations.

Real-time Processing: In dynamic environments, AI systems must process sensory data in real-time. Bounded rationality recognizes that there may be time constraints, and the AI system may need to make quick decisions with the information available at that moment.

Adaptability: Bounded rationality implies that AI systems need to be adaptable and flexible in their decision-making processes. As new information becomes available, the system may need to revise its decisions or update its understanding of the environment.

Cognitive Limitations: Just like humans, AI systems may have cognitive limitations that impact their ability to process and interpret sensory data. Bounded rationality in AI acknowledges these limitations and emphasizes the need for efficient algorithms and models that can operate within these constraints.

Literature review

Marwala, Tshilidzi. (2013). We revisit an extension of the bounded rationality theory called flexibly-bounded rationality in this study. Making judgments using rational methods necessitates employing defective and partial knowledge in conjunction with an intelligent machine that, if it is a person, is inconsistent. In limited rationality, the choice is taken within the confines of these restrictions, despite the fact that the information to be employed is partial and imperfect and that the human brain is inconsistent. The notion of flexibly-bounded rationality makes use of AI to make better judgements and sophisticated information analysis tools like the correlation machine to fill in any gaps in knowledge. Therefore, the scope of rational thought is broadened by the use of flexibly-bounded rationality. This study introduces the idea of marginalization of irrationality in decision making to address the challenge of satisficing when irrationality is present, given that human decision making is inherently illogical.

Bettis, Richard et.al. (2018). The Turing Award in Computing was shared by Alan Newell and Herbert A. Simon for their seminal contributions to the field of Artificial Intelligence. In addition to his Peace Prize, Simon took home the Nobel Prize in Economics for his work on "bounded rationality." The same core heuristic, "search till a satisfactory solution is found," was used in both instances. We suggest that the field of behavioral strategy has a lot to gain from the study of computational complexity and AI. These areas of study may strengthen the theoretical underpinnings of constrained rationality and the need for and use of heuristics. Last but not least, it may be helpful to apply a notion of "organizational intractability" inspired by the metaphor of the Theory of Computational Complexity to figure out which analytical decision-making tools are really unworkable in real-world settings due to time and management attention limits.

Nobre, Farley et.al. (2019) This article discusses a novel and cohesive viewpoint that helps participants (particularly the new economic men) in the organization push the limits of their reasoning. This view has its roots in the literatures of fuzzy logic, limited rationality, and cognitive psychology, all of which emerged about the same time in the second half of the twentieth century. This idea is bolstered by an interview with Professor Lotfi A. Zadeh (the founder of fuzzy logic) conducted in 2012 at the University of California, Berkeley. The study's findings suggest that (a) fuzziness, rather than probability, is the type of uncertainty that most pervades decisions in organizations; (b) fuzzy logic goes beyond bounded rationality by supporting the latter with new mathematics to solve non-programmed and ill-structured problems of unknown probability distributions; and (c) bounded rationality and fuzzy logic are complementary to one another.

Lieto, Antonio. (2019). In this article, I'll discuss the effects of Herbert Simon's concept of "bounded rationality" (first proposed in his book "Administrative Behavior") on the development of AI. I will show how the introduction of the cognitive dimension into the study of choice by a rational (natural) agent indirectly determined the development of a line of research in the AI field toward the realization of artificial systems whose decisions are based on the adoption of powerful shortcut strategies (known as heuristics) based on "satisficing" (i.e., non-optimal) solutions to problems. I will demonstrate how the "heuristic approach" to problem solving has been crucial in the development of AI and continues to be a valuable tool in the creation of smart systems.

Kato, Jefferson et.al. (2022). Trust may be seen as an investment game, in which one player takes the risk of betrayal from another in exchange for the potential for greater gain. Traditional game theory has led to several intriguing observations and conclusions, but it cannot foretell the presence of trust amongst individuals who are greedy and display maximizing behavior. However, trust is present in player decision making, as shown by research with these games. There are two goals for this paper. The first objective is to develop an agent-based economic model to demonstrate how the trust seen in these trials might originate from a rather elementary process. Using Epstein's suggested generative technique, we test the effects of natural selection, learning, and group formation on the creation of trust between agents. Second, the research tries to demonstrate that bounded rationality may be modeled by an AI algorithm, the learning classifier system (LCS), in an agent-based model, given that the studies indicate that the participants display limited rational behavior. This has led us to the conclusion that natural selection tends to select for more egocentric behaviors. Furthermore, learning and group formation boosted trust in our simulations, and when combined with natural selection, they were able to reverse selfish behavior. Results from these studies were consistent with the trust level predicted by the model with these three dynamics. The LCS's ability to simulate agents' constrained rationality may now be independently verified.

Bounded Rational and the Evolution of Go-Playing Computers

Most AI research focuses on two-player zero sum games with perfect information, like Go, Chess, and Checkers, where the connections between limited rationality and

AI are most obvious. Early on in the development of AI and game theory, these connections were clear. The German-speaking mathematical community's predominating interests in set theory and chess throughout the 1920s may be linked to John von Neumann's formulation of the Min-Max Theorem in the late 1920s. Von Neumann made contributions to computer science (von Neumann architecture) as well as economics (game theory and growth theory). Another founding father of computer science, Alan Turing (1953), focused on the possibility of using computers to play chess. In the 1950s, Herbert Simon conducted research on chess-playing algorithms and bounded rationality at the same time.

Table 1: The Complexity of Board Games

Game	Number of position reachable from stating position	Number of nodes in the smallest tree necessary to solve the game
Checkers	10^{17}	10^{32}
Othello	10^{30}	10^{58}
Chess	10^{50}	10^{123}
Go	10^{160}	10^{400}

Therefore, it should come as no surprise that Checkers was the first computer game to defeat world champions. It happened in 1990. When the ultimate result of flawless play was discovered in 2007, Checkers was fully solved (Schaeffer et al., 2007). Up until now, the most difficult games of Go and Chess have remained unsolved. Computer programs have advanced to the point where they can defeat world champions in Go (2016) and Chess (1997), but later than in Checkers. It is evident that as computer technology and software (algorithms) have advanced throughout time, so too have game-playing computer programs. A few significant turning points in the history of AI in gaming are included in Table 1. Three essential components have enabled advancements in AI application to games possible: knowledge, search, and learning. These constituents are interdependent. We'll talk about each of them in relation to artificial intelligence and constrained rationality.

The Complexity of Go: A Cellular Automata Perspective

A two-dimensional cellular automaton (CA)-like lattice of square cells may be used to depict the Go board (Figure 1). The arrangement of a Go board while it is in play is comparable to the condition of the cells in CA. This raises the issue of whether Go can be understood in terms of CA, and if so, what kinds of insights this approach may provide. This need to start with an explanation of what a CA is.

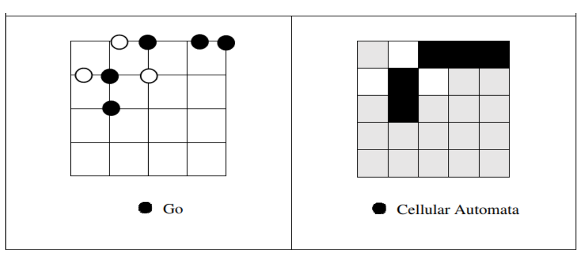

Figure 1: Go and Cellular Automata

The computational model known as the CA is composed of a lattice network of cells. Although Figure 3 shows the cells as squares, the cells of CAs may also resemble triangles and hexagons. The number of neighbors that a cell may interact with and be linked to is what gives various cell shapes their importance. The simultaneous changes in cell states brought upon by local interactions with nearby cells carry out computation. A local transition function specifies these interactions. For instance, the state of cell I or ci at time t+1 in a one-dimensional CA may be expressed as follows:

$$c_i(t+1) = c_{i-1}(t) + c_i(t) + c_{i+1}(t) \bmod 2$$

where ci+1 represents the neighbor on the right of cell i, ci-1 represents the neighbor on the left, and mod 2 represents the amount left over after dividing the total by two. This may be shown visually as:

c_{i-1}	c_i	c_{i+1}

In a two-dimensional CA with interactions with four neighbors (the von Neumann model), the transition function for a cell ci,j may be written as follows:

$$c_{i,j}(t+1) = c_{i-1,j}(t) + c_{i+1,j}(t) + c_{i,j}(t) + c_{i,j-1}(t) + c_{i,j+1}(t) \bmod 2$$

The following is a graphical illustration of this:

	$c_{i,j-1}$	
$c_{i-1,j}$	$c_{i,j}$	$c_{i+1,j}$
	$c_{i,j+1}$	

The transition function's regulations govern the dynamical development of CA cells' states. As a result, there are now four categories for CA:

- Class I: Fixed Point – where CA cells evolve to a uniformly constant state
- Class II: Periodic – where CA cells evolve toward continually repeating a periodic structure
- Class III: Chaotic – where CA cells evolve randomly
- Class IV: Complex – where the evolution of CA cells results in the production of localized structures that move and interact with one another

Figure 2 presents graphic representations of the four classes for one-dimensional CAs.

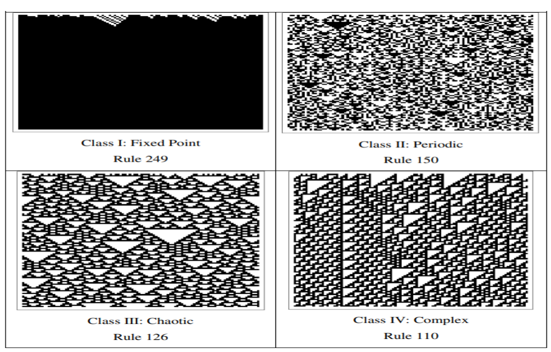

Figure 2: Four Classes of Cellular Automata

Even though four groups of CAs have been discovered by academics, there is still disagreement about the long-term development of these entities. Put another way, even if we are aware that there are four classes of CA, it is impossible to determine which rule (transition function) belongs to each class completely and a priori. This is not unexpected as the CA suffers from the Non-Halting Problem known to affect Universal Turing Machines since it is a universal computing machine. This has some fascinating ramifications for the game of Go. From the standpoint of the CA, a game of Go is similar to a computing process. However, there doesn't seem to be an analogous transition function that controls the progression of a Go games, unlike CA. The objective of territorial control and the rules of Go are the closest things to a transition function. AI self-playing algorithms explore the Go world according to these rules and objectives. However, the undecidability of CA evolution does seem to imply that, despite the possibility of AI programs surpassing human abilities in Go, these programs will not be able to solve the game through self-play in a way that will allow them to identify a single self-play game that yields global optimality. Because of this, artificial intelligence (AI) machines will always remain machine-bounded rational, and even if they can beat human world champions who are also machine-bounded rational, they will never be able to solve the game of go.

Conclusion

The concept of bounded rationality in the context of artificial intelligence (AI) and sensing highlights the inherent limitations that AI systems face in making decisions based on incomplete information, resource constraints, and cognitive limitations. This recognition is crucial for developing practical and effective AI systems that can navigate real-world environments. Here are key takeaways:

Realism in Decision-Making: Bounded rationality brings a sense of realism to AI decision-making. Acknowledging the limitations in access to information and resources allows developers and researchers to design systems that can operate effectively in imperfect and dynamic environments.

Adaptability and Flexibility: AI systems embracing bounded rationality need to be adaptive and flexible. They should be capable of adjusting their decisions based on evolving information, emphasizing the importance of continuous learning and updating of models as new data becomes available.

Efficient Resource Utilization: Resource constraints are a fundamental aspect of bounded rationality. AI systems must prioritize and efficiently allocate computational resources, energy, and processing power to maximize their effectiveness within the given limitations.

Real-Time Decision-Making: In dynamic scenarios, quick decision-making is essential. Bounded rationality underscores the need for AI systems to process sensory data in real-time, even if it means making decisions with incomplete information to respond promptly to changing environmental conditions.

Human-Like Decision Processes: Bounded rationality aligns AI decision-making with human cognitive processes, recognizing that both humans and machines operate under constraints. This similarity enhances the interpretability of AI decisions and fosters collaboration between humans and AI systems.

Algorithmic Efficiency: Developing algorithms that can operate efficiently within the constraints of bounded rationality is a key challenge. Designing models that balance accuracy with computational efficiency is essential for the practical deployment of AI systems in various applications.

In summary, embracing bounded rationality in AI to sensing is essential for creating intelligent systems that can navigate the complexities of the real world. By understanding and working within the limitations imposed by incomplete information and resource constraints, developers can design AI systems that are not only technically robust but also capable of making decisions that align with the practical demands of dynamic environments.

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