Simulating Boyd's OODA Loop: Towards an ABM of Human Agency and Sensemaking in Dynamic, Competitive Environments

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***Abstract*-Increasingly complex global scenarios require advanced simulations of human decision-making. Existing models often neglect the nuanced cognitive processes essential in dynamic environments, leading to oversimplified analyses. Leveraging John Boyd's conceptualization of the Observe, Orient, Decide, Act (OODA) loop, we propose a novel, agent-based simulation exploring human agency and sensemaking within evolving competitive landscapes. By endowing agents with diverse cognitive capabilities across the OODA spectrum, we dissect the nuanced impacts of heterogeneous information processing and cognitive strategies on agent fitness and survival. While Boyd emphasized the strategic advantages of swiftly navigating the OODA loop or infiltrating an opponent's loop, we also explore the effects of diverse information processing and cognitive abilities on agent fitness. Central to our initial findings is the critical significance of the Orient and sensemaking phase, which emerges as a decisive factor in surpassing the mere possession of information, collection of data or swift and efficient execution of decisions and actions. We present several scenarios—ranging in complexity and resource availability— that underscore the superiority of deep sensemaking over other cognitive capabilities. Although only an initial step, we believe such approaches can expand both OODA loop's theoretical underpinnings and its practical relevance in enhancing strategic decision-making processes for human, behavioral, social, and cultural phenomena.**

Keywords-Agent-Based Modeling (ABM); OODA Loop; Complex Adaptive System; Co-Evolution.

I. INTRODUCTION

The concept of the Observe, Orient, Decide, Act (OODA) loop [2], introduced by Colonel John Boyd in the military context, has transcended its original domain and found applications in various fields, including human decision-making. The theoretical underpinnings of OODA loops in human decision-making stem from Boyd's original framework, which emphasizes the iterative and dynamic nature of decision-making. According to Boyd, individuals continuously cycle through the phases of observation, orientation, decision, and action, with each iteration informing subsequent cycles. This dynamic process enables individuals to adapt to changing circumstances and outmaneuver opponents effectively. Our research seeks to understand how variations in cognitive capabilities within the OODA loop affect strategic decision-making, and to explore the implications of these variations for achieving strategic advantage and survival in competitive environments.

Empirical research supports the efficacy of OODA loops in enhancing human decision making across various domains. For instance, in a study by González et al. [11], participants engaged in a simulated decision-making task involving time pressure and uncertainty. The results revealed that individuals who followed the OODA loop sequence exhibited faster response times and higher decision accuracy compared to those who adopted linear decision-making strategies. Similarly, in a neuroscientific investigation, Voss et al. [22] used functional Magnetic Resonance Imaging (fMRI) to examine the neural correlates of the OODA loop phases during decision-making. They found distinct patterns of brain activity associated with each phase, suggesting that the OODA loop framework corresponds to underlying cognitive processes in the brain. Furthermore, organizations can leverage OODA loops to enhance their decision-making processes and gain a competitive edge. By fostering a culture of rapid feedback and learning, organizations can adapt more quickly to market changes and exploit opportunities faster than their competitors [21].

In this paper, we agentize Boyd's OODA loop across each step of the process to simulate human agency and sensemaking under dynamic, competitive environments. We do this by varying agents' cognitive abilities in each step of the process. For Observe, we allow for different discrete levels of sensing their environments, ranging from local to global information. For the Orient step, we create two interactive vectors of cognitive abilities, one embracing determinism to stochasticity while the other focuses on the increasing complexity of mental models, to create a typology of twelve different mental models to make sense of competitive environments. For the Decide step, we instantiate three different levels of increasingly complex decision trees to capture various levels of agency. For the Act step, we then allow agents to execute their decision tree calculus with varying costs and time horizons. We then setup both single and double loop learning to occur, given agent OODA loop execution fitness scores. This enables us

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to explore agents' cognitive abilities both across and within each step of the OODA process.

The application of OODA loops in real-world decision-making contexts offers several practical benefits. One such benefit is improved decision agility, as individuals can rapidly cycle through the OODA loop to respond effectively to evolving situations. This capability is particularly valuable in dynamic and uncertain environments, such as emergency response operations [9]. Furthermore, organizations can leverage OODA loops to enhance their decision-making processes and gain a competitive edge. By fostering a culture of rapid feedback and learning, organizations can adapt more quickly to market changes and exploit opportunities faster than their competitors [2].

However, speed of OODA loop execution alone is only one small element: we focus on varying information and cognitive capabilities within each step of the loop to explore their respective implications for learning, competition, and efficiencies in dynamic environments. Below we outline our simulation approach, architecture and begin exploring its capabilities through running several scenarios across different dynamic resource landscapes as well as Simple, Moderate and Smart cognitive agents. While we only offer some initial findings, we believe that empirically calibrating and extending agentized OODA approaches such as this can provide significant insights into human agency and sensemaking in dynamic, competitive environments.

The rest of the paper is structured as follows. In Section II, we present the related works. In Section III, we present the model design. In Section IV, we present the model results. Finally, we conclude our work in Section V.

II. Related Works

A. OODA

In 1987, John Boyd originally developed the OODA loop as a decision-making model that could be applied in any competitive environment, be it military or business. This model encompasses four pivotal stages—Observe, Orient, Decide, Act—through which individuals continuously cycle, allowing each cycle to build upon the insights of the previous ones. This dynamic process enables individuals with environmental sensemaking and agency to adapt to changing circumstances and outmaneuver opponents effectively. Figure 1 outlines Boyd's steps, with feedback loops for single "input-output" learning and double loop learning where outcomes can also foster change to specific OODA steps' cognitive abilities given success or failures.

First, observe the environment to gain new information. This includes collecting immediate sensory information as well as more abstract data, such as changes in the competitive landscape or shifts in social dynamics. The objective of this step is to create a comprehensive snapshot of the current situation to inform subsequent decisions and actions [7]. Observation can be achieved through various means, including direct sensory perception, the use of technological tools (e.g., radar, surveillance systems), the collection of big data, open-source information, intelligence espionage, etc. [6]. In the military domain, Boyd emphasized the importance of rapid and accurate observation capabilities to gain a strategic advantage over adversaries [17].

Second, combine this new information with previous experiences, culture, and mental models to "Orient" and get an understanding of the current situation [4][5]. Orientation is the most complex and critical part of the OODA loop because it sets the context for decisions and actions. It involves filtering and processing the observed information through a framework of existing knowledge, experiences, and expectations [13] [15]. This step determines how individuals and organizations interpret their environment, assess threats and opportunities, and consider potential actions. In their study, Klein et al. [16] extended Boyd's framework by highlighting the role of mental models in the orientation phase. They proposed that individuals' decision-making processes are shaped by their mental representations of the environment, tasks, and goals. These mental models influence how individuals perceive, interpret, and respond to information, thereby affecting the effectiveness of their decisions. Orientation methodologies encompass cognitive processes, including situational awareness, mental simulation, schema activation, and decision-making under uncertainty. These processes are influenced by a myriad of factors, including training, cultural background, personal experiences, and the specific nature of the information received.

Third, review the options to determine the best course of action. The "Decide" step is a critical phase in John Boyd's OODA loop framework, acting as the bridge between understanding the situation (Orient) and taking action (Act). This step involves making a decision based on the analysis and synthesis of information collected during the Observe and Orient phases, under both risk and uncertainty [14]. The decision-making process is where strategies, tactics, or plans are formulated before being implemented in the Act phase. The "Decide" step is where choices are made about which course of action to take. This step is crucial for effective execution, as it determines the direction that actions will take. The quality of the decision-making process directly influences the outcome of the OODA loop, making it a pivotal point in the cycle. Decision-making methodologies in the context of the OODA loop can include analytical models, intuition-based approaches, decision theory, game theory, and scenario planning, among others depending on levels of uncertainty and risk. The chosen methodology often depends on the complexity of the situation, the amount of information available, and the time constraints faced by the decision-maker.

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Finally, upon deciding, the chosen action is implemented. In the OODA loop, the "Act" step is where theory and planning confront reality. It's the execution phase where strategies and decisions are translated into concrete actions with the aim to achieve a desired outcome. This step is critical for the loop to be effective, as it is the point at which the individual or organization interacts directly with the environment to effect change. The methodologies for action can vary widely depending on the context, ranging from military operations, where it could involve maneuvering forces or engaging targets, to business strategies, where it might involve launching a new product or adjusting marketing tactics. The key is to act in a manner that is both timely and relevant to the information and orientation developed in the earlier steps of the OODA loop.

Although referred to as the OODA loop, in reality, it functions not as a circular process with independent steps but as a continuous operation [17], across multiple interconnected and coupled steps to produce outcomes. Since its introduction, it has become a popular framework for decision-making, especially under uncertainty [18]. Boyd identified several keys to success, including getting inside your opponent's OODA loop or running through your OODA loop more efficiently [3].

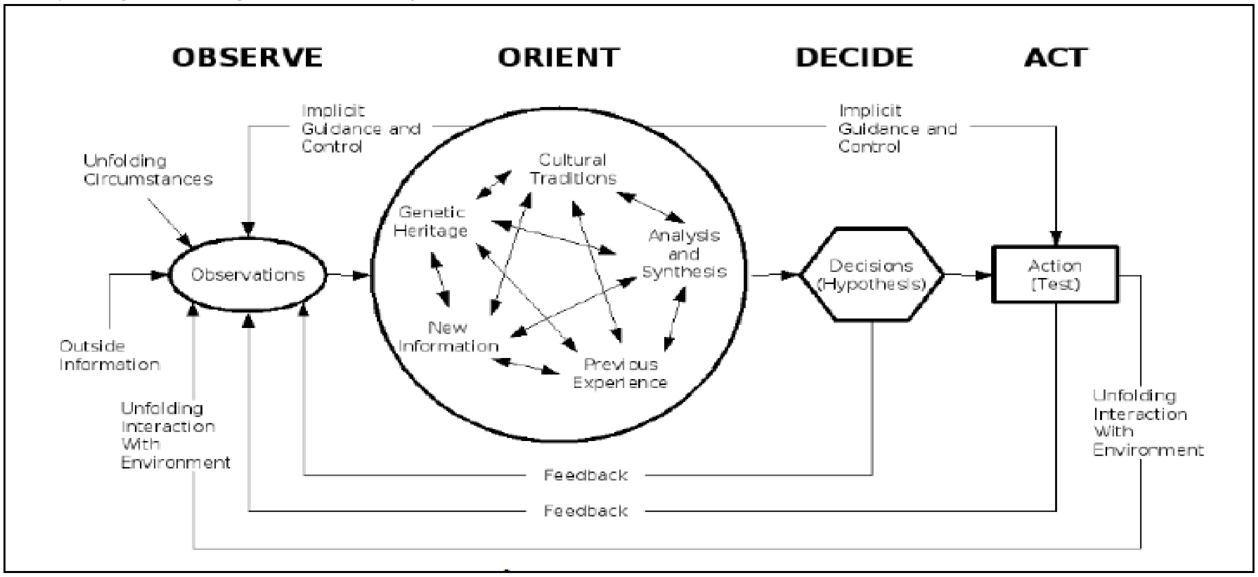

Figure 1. Boyd's OODA Loop [10].

B. An Agentized OODA Model

With the massive improvements in computational power and the popularization of agent-based modeling given complexity theory, the past several decades have seen many forays into simulating decision-making within complex adaptive systems [2][8][12][19]. These models employ a mix of game theory, rationality, and learning to simulate decision-making in dynamic complex systems under uncertainty [23]. Even relatively simple games, such as the El Farol problem, can yield intriguing results, unveil new strategies, and dynamic equilibria with slight increases in complexity [2][20]. Single-Loop and Double-Loop learning add a crucial dimension to these models, enabling actors to adapt to changing environments and optimize their fitness functions [24].

Complex adaptive systems are pervasive throughout the world, in domains such as business and military, and inherently operate under significant uncertainty and time constraints. Heterogeneous agents, by optimizing their fitness functions, create meso-level competitive social dynamics. These dynamics, in turn, shape macro-outcomes that influence decisions at all levels, both present and future [1]. Observing these interactions within a dynamic landscape, alongside agents' single and double-loop learning processes, offers opportunities to identify emergent, non-linear behaviors and potentially, resulting novel strategies. It also highlights the critical impact of varying agent capabilities across outcomes.

III. MODEL DESIGN

Figure 2 provides an overview of our agentized system. Individuals possess varying cognitive capability values on each one of the OODA vectors that influence their overall decision-making processes. These instantiate into local competitions on varying environmental landscapes, directly influencing outcomes and thereby increasing or decreasing agent wealth. The magnitude of these gains or losses triggers positive or negative feedback loops, prompting agents to update their capabilities given learning and expectations. This adaptation is crucial for their survival in dynamically evolving landscapes.

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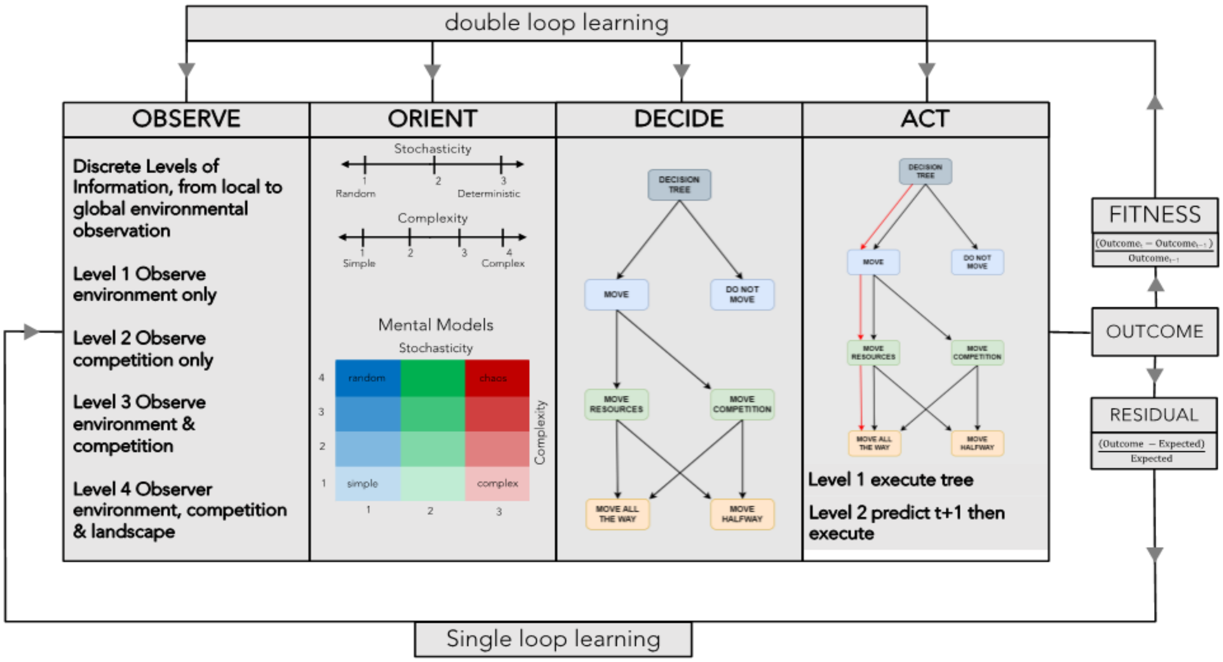

Figure 2. Agentized OODA Loop Architecture.

The Observe phase is a critical conduit for information gathering, enabling agents to perceive their local environment, competitors, and landscape. At the most basic levels, agents can either identify the resources available in each area or the positions of other agents within the local environment. Consequently, agents have three critical pieces of information to consider in the Orient step, encompassing resources, agent positions, and local landscape that influences their strategic planning. This provides four different discrete Observation levels for agents in Figure 3.

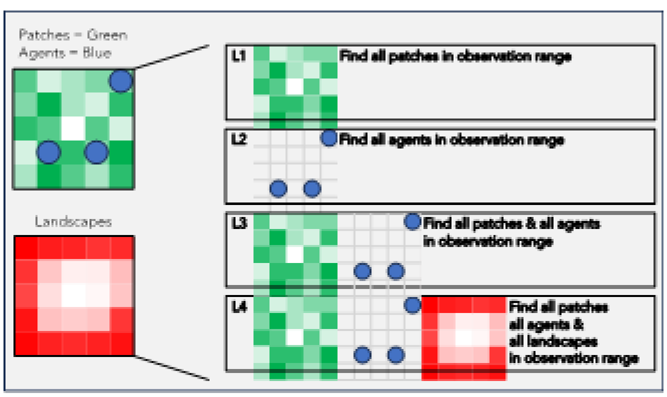

Figure 3. Observation Module Types and Level.

The Orient phase comprises two components: complexity and stochasticity, which together create a matrix of various mental model levels that determine how agents perceive their current situation. Agents' complexity value determines the equation into which observed values are input, ranging from a simple mental model of $Y_t = Y_{t-1}$ where the past experiences will be the same as future, to complex specifications where $Y_t = Y_{t-1} + X_{1t-1} + X_{2t-1} \ldots + X^p{}_{kt-n}$ to incorporate more complex past history and exogenous polynomial expressions. The stochasticity value influences the degree of random noise or interference added to each equation, reflecting the spectrum of uncertainty or misperceptions from deterministic (no impact) to entirely random (total impact). Figure 4 illustrates how various combinations of complexity and stochasticity influence the equations underlying the mental models.

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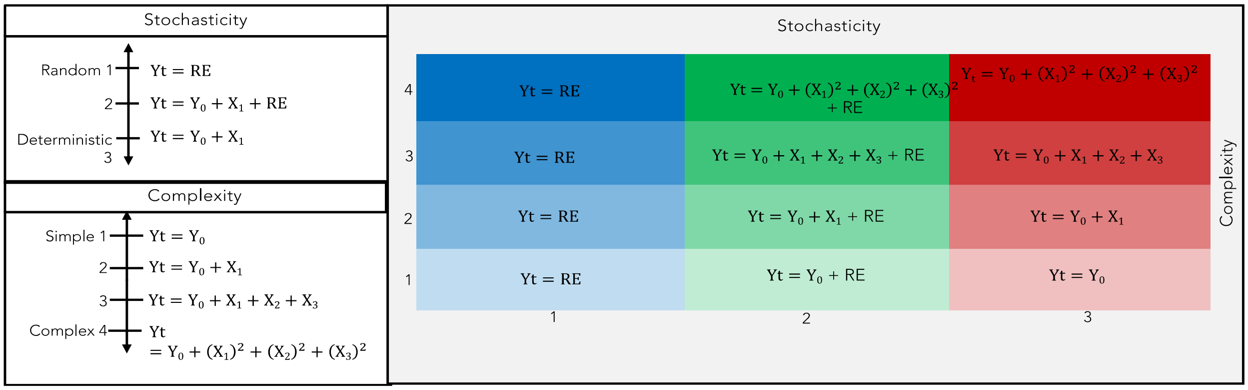

Figure 4. Orient Module Vectors of Randomness and Complexity for Mental Model.

The Decide phase presents agents with decision trees that vary in complexity from simple, single-level trees to more complex structures with three levels as shown in Figure 5. With each additional level, the decision tree expands, offering a broader set of choices for the agents to consider. At the simplest level, agents decide whether to move or not, with an associated move cost. Increasing cognitive decision capabilities, at the next level agents can decide to move towards desirable resource locations or move towards competitors. At the highest cognitive decision level, agents evaluate complex decisions: whether to stay put, move away from competition, approach resources, and whether their movement should be full or partial given costs and competitors.

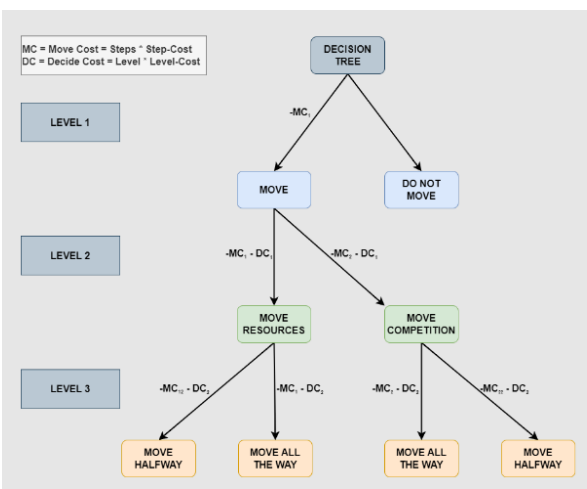

Figure 5. Decide Module Decision Tree Calculus and Depth.

The Act module enables agents to navigate their decision tree to identify optimal courses of action that maximize expected utility. Simpler agents process the decision tree, evaluating each potential decision's outcomes and costs before selecting the action that yields the greatest expected utility. If agents have additional capacity, they can anticipate the future landscape at time *t+1*, and act strategically by integrating foresight into their decision tree to refine their strategy before executing the course of action. This strategic foresight allows the agents to identify the competitive landscape of their destination patch and update the expected utility of the destination accordingly.

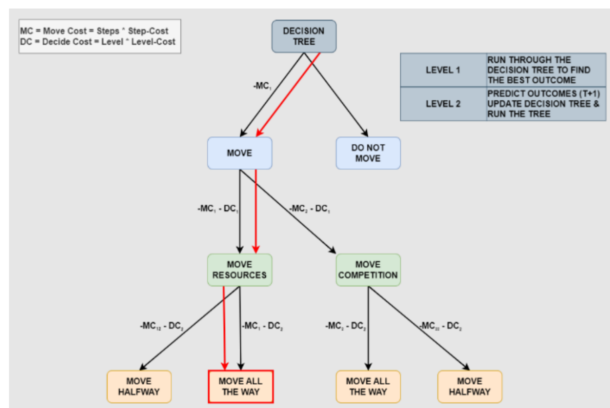

Figure 6. Act Module Decision Tree Calculus.

After progressing through the OODA loop, an agent executes its action: either moving or capturing resources. The discrepancy between an agent's expected and actual outcome dictates the feedback loop, influencing how agents update their mental models. Minimal or no discrepancies between agent outcomes and expectations, signify slight improvements or deteriorations in fitness, and result in the absence of single-loop learning. Significant discrepancies between expected and actual outcomes present single-loop learning opportunities, prompting agents to adjust the Orient phase to more closely align with reality.

For double-loop learning, the rate of change in outcomes dictates the frequency, strength, and type of feedback. Small changes in outcomes do not trigger feedback, whereas significant changes can lead to either positive or negative feedback learning opportunities. Positive feedback leads the agent to further enhance the capacity of the OODA step it last improved, provided it has not reached its maximum. Negative feedback prompts the agent to roll back any previous enhancements in capacity. Through the interplay of single-loop and double-loop

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learning capturing ‘lessons learned’ agents can adeptly navigate a dynamically evolving landscape, adjusting to changes in environmental resources and the co-evolution of competitors to optimize their fitness functions.

IV. RESULTS

A. Baseline

Here, we first establish a baseline to gauge typical performance of agents within our OODA simulation, setting the standard for comparison. This baseline involves generating normal distributions for the initial values of each individual OODA component. To ensure a realistic environment, we craft a landscape that maintains a balance between scarcity and abundance of resources.

We employ various scenarios that deviate from this baseline to examine how agents respond to shifts in agent capabilities and environmental factors. These scenarios are critical for evaluating the robustness and adaptability of the agents' decision-making processes. These scenarios are assessed using metrics that measure resource management, survival, and decision-making capability, offering insights into the effectiveness of cognitive strategies within the OODA loop. By comparing agent performance across these varied scenarios with the baseline, we draw nuanced conclusions about the efficacy of different strategies embedded in the OODA loop framework.

TABLE 1. BASELINE INITIAL CONDITIONS AND PARAMETER VALUES

Parameters	*Description*	*Base value*
Population	Total number of agents	25
Agent Resources	The initial number of resources for agents	75:25
Environment Resources	The initial number of resources for environment	75:25
Observation Range	How many steps the agents can see around them	4:1.25
Move Cost	The resource cost for agents to move one step.	1
Regrow Time	The number of ticks it takes for the environment to regrow their resources.	1
Energy Loss	An absolute attrition value in resources for agents each tick.	1
Observe Score	The Observe Step score of agents	2.5:0.75
Complexity Score	The Complexity Step score of agents	2:1
Stochasticity Score	The Stochasticity Step score of agents	1.5:0.75
Decide Score	The Decide Step score of agents	2:0.5
Act Score	The Act Step score of Agents	1.5:0.25

Figure 7 below depicts four separate simulation plots. The first one is the starting environment given initial conditions. Agents are yellow circles, with the color indicating their overall sum of their OODA scores, lighter colors indicate lower values, while darker hues signify higher values. The environment is characterized given resource density, with higher resource values in darker shades of blue. The second plot is a phase portrait of the populations’ average summed OODA score by their average fitness score outcomes. The third times series plot details Simple, Moderate and Smart agents’ average fitness outcomes over 1000 iterations. Finally, the last plot shows the resulting environment and competitive landscape at the end of the simulation.

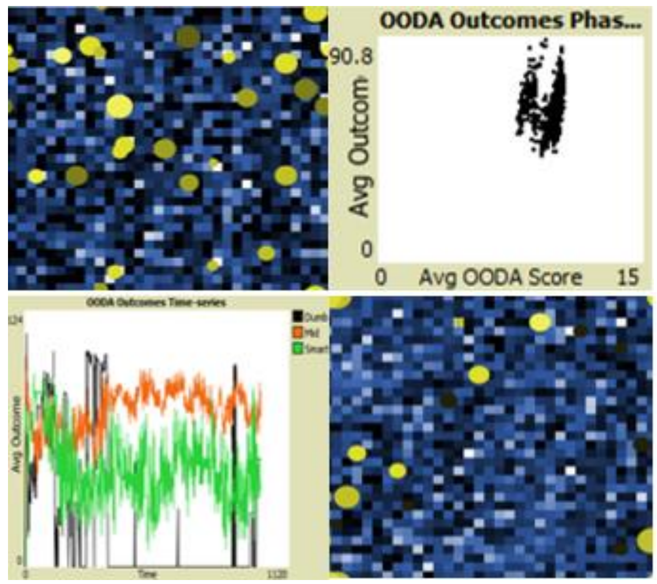

Figure 7. Baseline Environment, Time Series and Phase Portrait Plots.

In our baseline scenario, agents quickly reach equilibrium within the first two hundred iterations, with Simple agents perishing and Moderate and Smart agents achieving relatively stable, but oscillatory fitness outcomes. Moderate agents consistently emerge as the most successful agent type, having the highest average outcome on fitness scores. The phase portrait illustrates that agents quickly identified and adhered to a stable equilibrium, with the average OODA score hovering around 8, indicating little double loop learning. This suggests that the agents are capable but not maximally intelligent and stop learning early. The time series plot reveals a population bifurcation of OODA scores: a few extremely smart agents with the highest scores survive, alongside a larger group of agents with moderate intelligence. Diving into individual module score details, interestingly for Observe, Decide, and Act components, agents do not require the highest capacity scores to survive. This demonstrates that rather than having additional capacity to observe the landscape, decide among more options, or predict one step into the future, the most critical ability for agents is synthesizing observations using the highest capability mental model and is consistent with prior literature. Simply put, agents that lack sensemaking

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orientation of their environment, despite access to information, decision-making process and action execution, do not survive.

B. A Low Resource Landscape

We define the first scenario by modifying the baseline conditions to create an environment with scarce resources and increasing energy loss. Previously, the environment had resource ranges from 25 to 125 units; this has been adjusted to 0 to25. Additionally, we have doubled the energy loss of move costs from 1 to 2. This creates a harsher, more competitive environment as agents must now vie for a significantly reduced pool of resources.

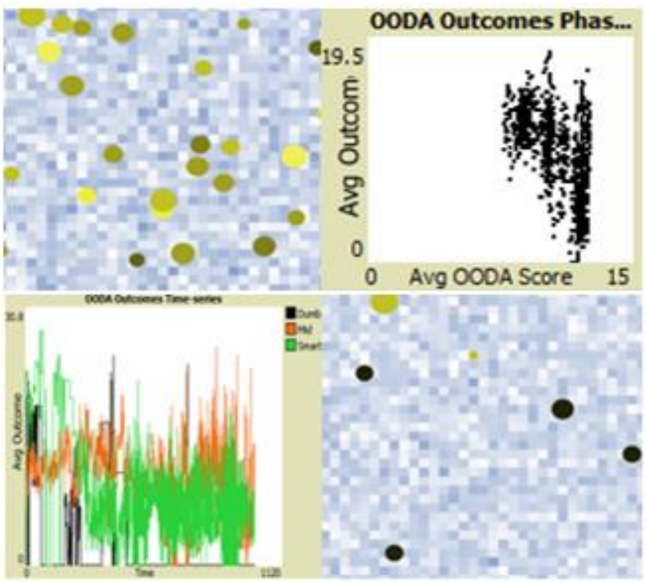

Figure 8. Scenario 1 Environment, Time Series and Phase Portrait Plots.

In this challenging scenario, only six agents survive: four are classified as Smart and two as Moderate in overall summed OODA score intelligence. In this harsh landscape, while Smart agents have a higher survival rate, Moderate agents achieve slightly better outcomes, though by a smaller margin than the baseline. Under this scenario, survival is exclusive to agents with the highest capacity for Orientation. The most complex equation and no noise are required to survived. Contrary to the baseline scenario, a premium is placed on the observational ability, as evidenced by most agents possessing the highest Observe scores. Decision and Act capacity remains low, as agents survive and thrive by being reactive quickly. Also, Smart agents remain stationary, exploiting resources from their immediate location given higher move costs in a resource poor environment. Conversely, Moderate agents actively seek out better resources while incurring higher costs.

C. Low Resource Landscape with Global Knowledge

In our second scenario, agents have the added advantage of perceiving a significantly wider environmental range while maintaining the same harsh environment as in the above scenario. Previously limited to a view range of 0 to 5, agents can now perceive an expanded range of 0 to 20. This dynamic aims to explore how balancing the challenging environment with the agents' enhanced global environmental Observe capabilities affects their mental models and leads to the evolution of agents optimized to maximize their fitness function. Such adaptations parallel the evolution technology to increase human situational awareness.

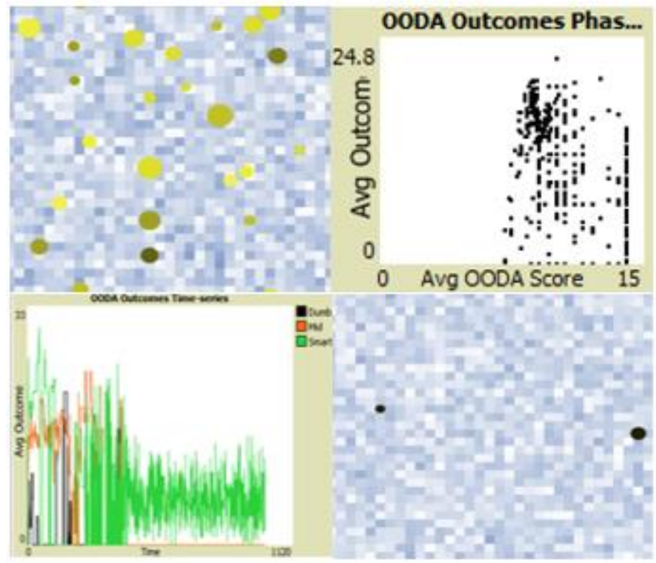

Figure 9. Scenario 2 Environment, Time Series and Phase Portrait Plots.

Here, we see Smart agents dominating the landscape, in contrast to Moderate and Simple agents who exhaust themselves in an attempt to capture all possible gains by expending excessive energy. Smart agents leverage their superior OODA summed capacity to accurately assess the landscape, recognizing the advantage of patient anticipation over frantic movement in this harsh, resource poor environment. Although they do not surpass Moderate agents' early gains during the simulation, they maintain consistency in fitness outcomes. This consistency may highlight additional benefits of Decision and Action phases, empowering agents with a considerably broader range of strategic courses of action.

D. Harsh World, Smart Agents

Given observed difficulties agents face in challenging environments, we now adjust the scenario to agent at high levels of summed OODA intelligence. Within their observation range, which remains extensive, each agent can now perceive all other actors, resources, and landscapes. Each agent also consistently employs the most sophisticated mental model available. Each agent can use the full decision tree to see which option is best. Finally, each agent can see the best outcome with the next tick in mind, inducing strategic behavior.

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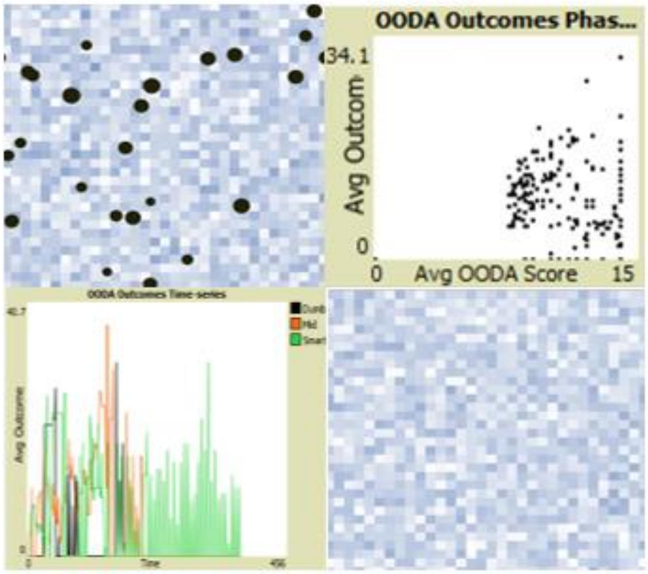

Figure 10. Scenario 3 Environment, Time Series and Phase Portrait Plots.

Even with the above cognitive advantages, this harsh environmental scenario proves too challenging for long term fitness achievement and survival. In a multitude of simulation runs, all agents inevitably perish within the first few hundred iterations. Agents consistently exhibit low average outcomes, demonstrating their inability to sufficiently adapt to the landscape. Actors with the highest OODA scores incur significant costs due to the increased complexity of their decision-making processes. This complexity makes each action more resource intensive as they navigate their decision trees. In a resource poor environment, the cost of strategic complexity is high.

E. Harsh World, Simple Agents

Building on the above, our final scenario assesses agent performance given with the lower OODA capacities in harsh, resource poor environments.

In the same extremely harsh environment, agents with low OODA scores demonstrate performance comparable to that of their more sophisticated counterparts. Whereas Smart agents employ complex models and strategize to endure difficult environments for future gains, agents with minimal OODA capacities react more spontaneously. However, given resource scarcity and competition costs, these produce almost equally ineffective outcomes on fitness scores.

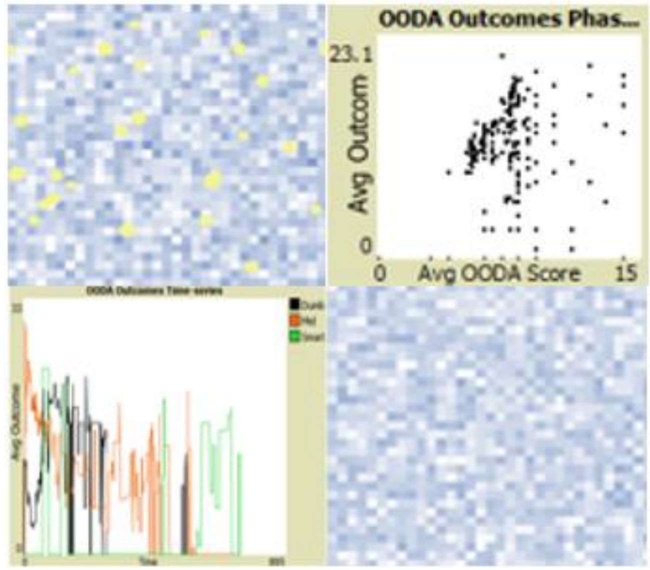

Figure 11. Scenario 4 Environment, Time Series and Phase Portrait Plots.

V. CONCLUSION

In this paper, we set out to explore cognitive simulation capabilities, by agentizing Boyd's OODA loop in a dynamic, competitive environment. By specifying and controlling cognitive abilities in each OODA module, we focused on fitness outcomes based upon varying levels of capabilities at each step. Our findings demonstrate that this approach opens a myriad of simulation possibilities. Furthermore, we observed the interactive effects of increasing or decreasing cognitive capabilities.

Some of our next steps include extending scenarios to include adding varying degrees of agent competition across dynamic resource landscapes to further calibrate OODA modules and feedbacks. Once complete, we will perform quasi-global sensitivity testing to extract key model drivers and dependencies to make inferences on cognitive behavior across each OODA step. This also allows detailed exploration of both single and double loop learning mechanisms across different competitive environments.

We believe the development of OODA loops for human decision-making represents a significant advancement in understanding and improving decision-making processes. Building on Boyd's original framework, many other researchers have validated the foundations, provided empirical evidence, and outlined practical implications for incorporating OODA loops into multiple domains and contexts. By explicitly embracing the dynamic and iterative nature of human decision-making, hopefully both individuals and organizations can enhance their ability to navigate increasingly complex environments.

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