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

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Introduction

- OODA Loop:
  - Developed by military strategist John Boyd.
  - Comprises four iterative phases: Observe, Orient, Decide, Act.
  - Used to model decision-making processes in dynamic and competitive environments (Military, Business, Politics, etc.).

- Motivation:
  - Global scenarios are becoming increasingly complex, requiring advanced simulations of human decision-making.
  - Exploring the impact of diverse information processing and cognitive strategies on agent fitness and survival.

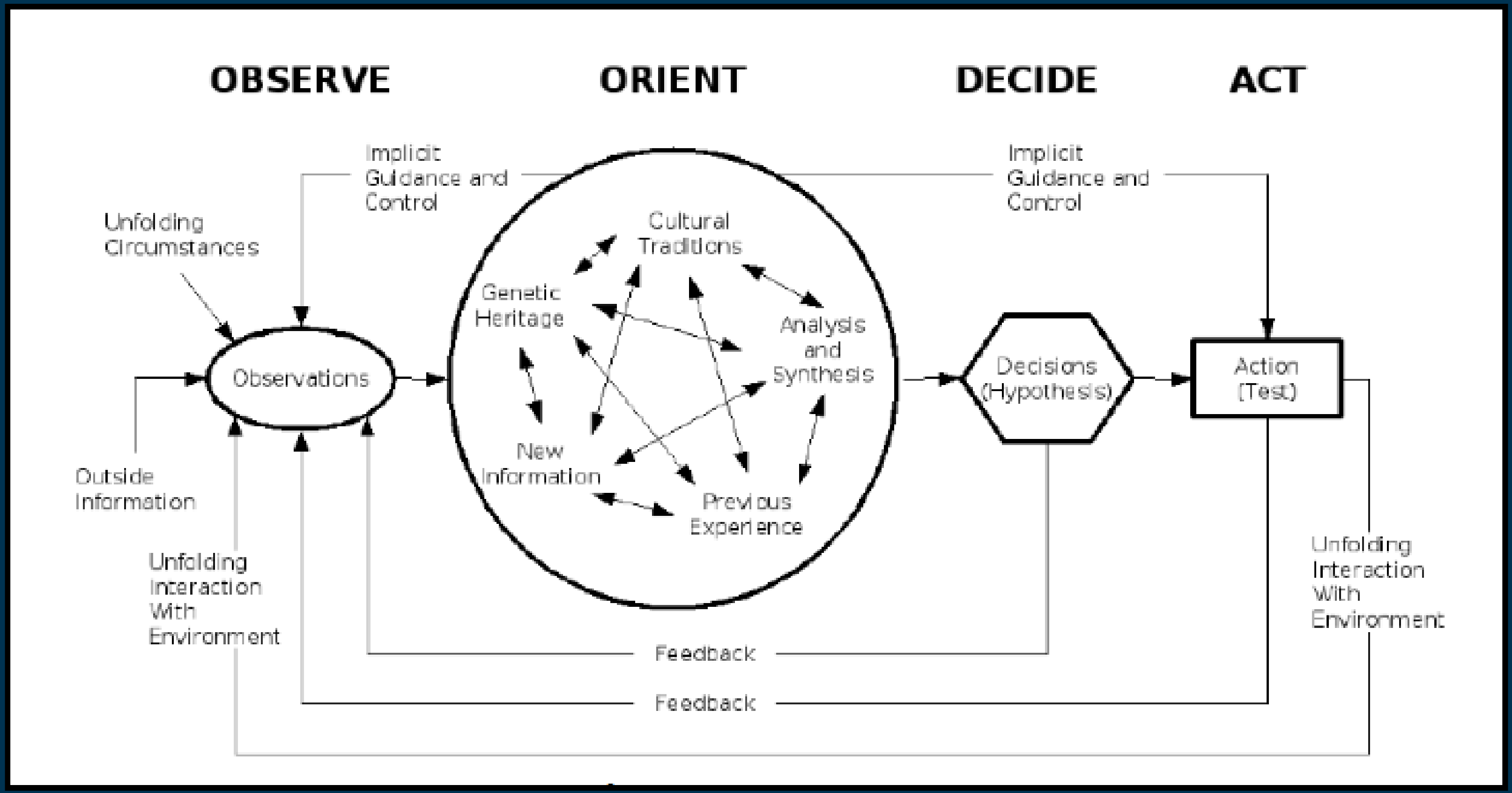
Research Objective

- Objective:
  - Investigate how variations in cognitive capabilities within the OODA loop affect strategic decision-making.
  - Develop an agent-based model (ABM) to simulate human agency and sensemaking in dynamic, competitive environments.
- Key Questions:
  - How do different levels of information processing and cognitive strategies influence agent fitness and survival?
  - What role does each OODA phase play in achieving strategic advantage?
- Significance:
  - Provide practical insights for improving decision-making processes in various fields (e.g., military, business, policy-making).

Background and Literature

OODA Loop

- Observe:
  - Gather information from the environment.
  - Collect sensory data and abstract information (e.g., changes in the competitive landscape).
- Orient:
  - Analyze and synthesize observed information.
  - Integrate new data with existing knowledge, experiences, and cultural context.
- Decide:
  - Formulate strategies, tactics, or plans.
  - Determine the best course of action based on the oriented information.
- Act:
  - Implement the chosen action, executing decisions precisely within the environment.
- Feedback:
  - Conduct single and double-loop learning to continuously update our understanding of the world, allowing for adaptation and improvement

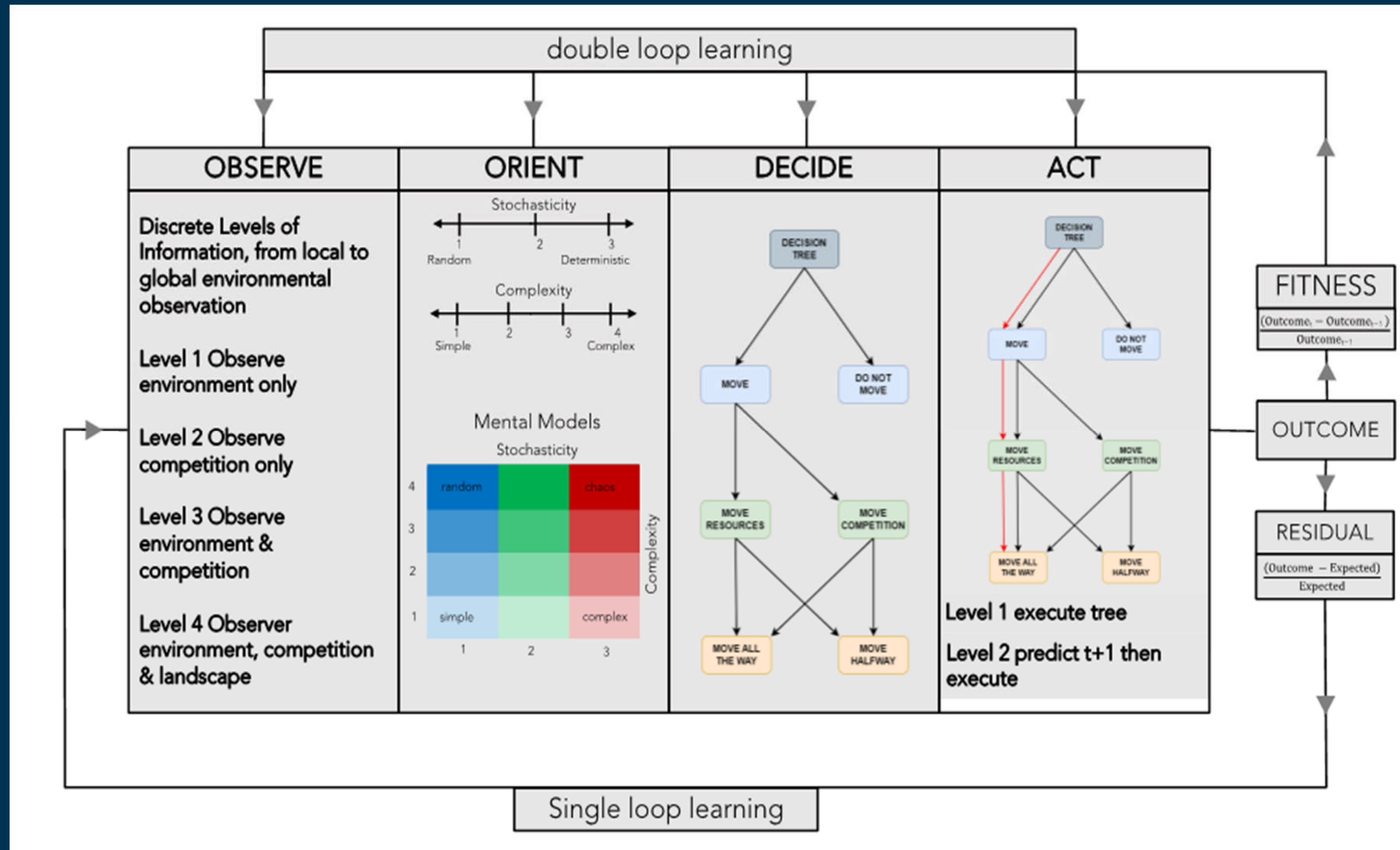


Frost 2012

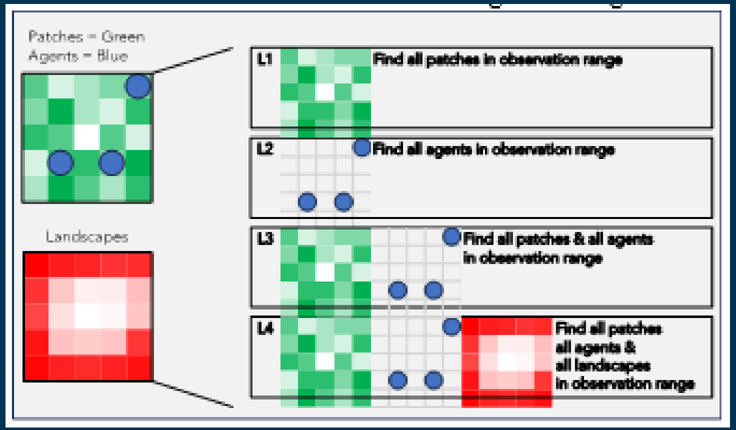
Model Design

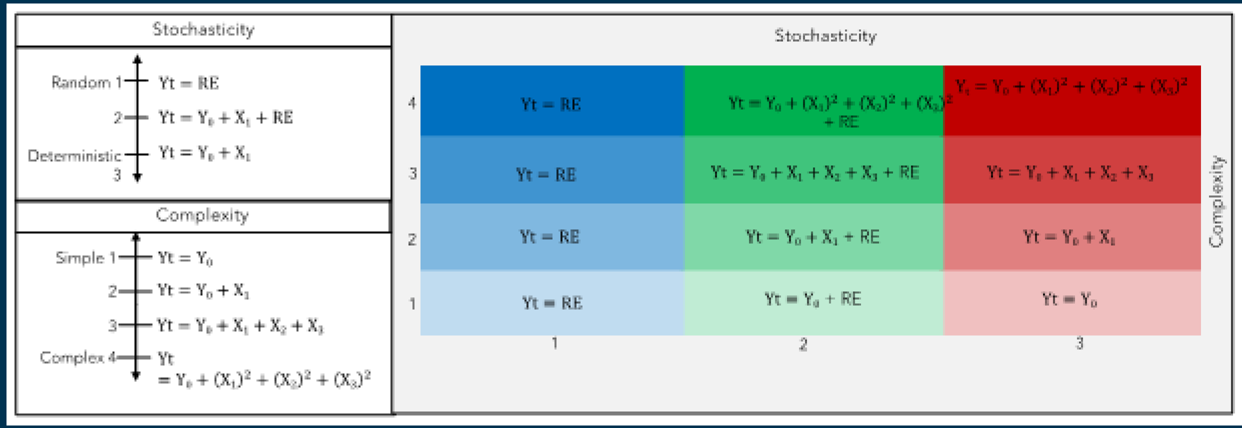
Our OODA Model

- Agent-Based Modeling (ABM):
  - Simulation approach to model complex systems using simple rules and heterogenous agents.
  - Agents represent entities with distinct cognitive capabilities.
- Model Components:
  - **Observe**: Agents have varying levels of information sensing from local to global.
  - **Orient**: Agents possess different mental models, ranging in complexity and randomness.
  - **Decide**: Decision trees with varying depths and complexities to simulate decision-making.
  - **Act**: Agents execute decisions with varying costs and time horizons.
- Learning Mechanisms:
  - **Single-Loop Learning**: Agents update their strategies based on discrepancies between expected and actual outcomes.
  - **Double-Loop Learning**: Agents adjust their cognitive models and strategies based on the rate of change in outcomes.



Observe & Orient

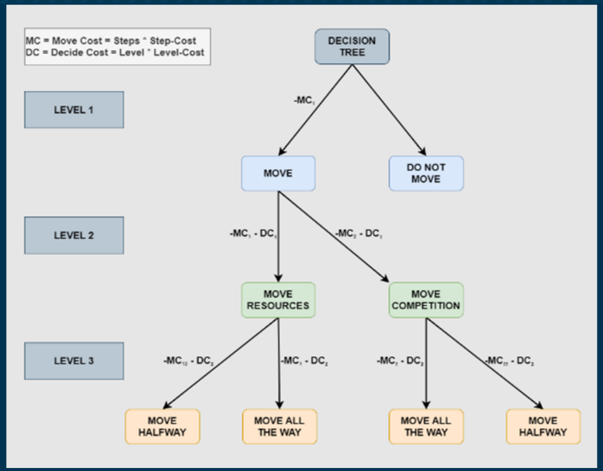




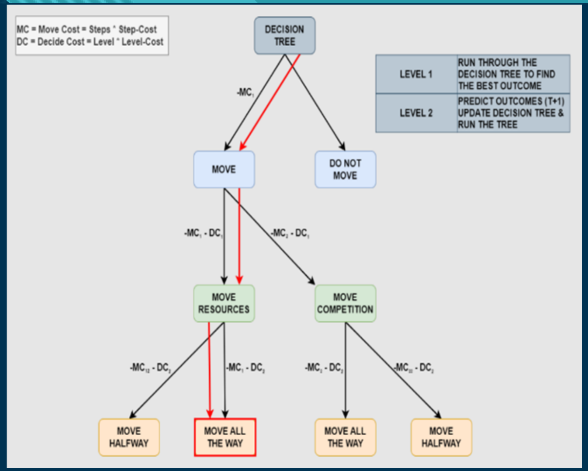
- **OBSERVE**: Agents collect data from their environment.
- Observation Levels:
  - Level 1: See all resources nearby
  - Level 2: See all agents nearby
  - Level 3: See all agents and resources
  - Level 4: See all agents, resources, and the environmental landscape.

- **ORIENT**: Agents analyze and synthesize observed information.
- Mental Models:
  - Complexity: Range from simple past experiences to complex, multi-variable models.
  - Stochasticity: Degree of randomness or noise in the mental models.
- Vectors of Orientation:
  - Deterministic to stochastic processes.
  - Simple to complex mental models.

Decide & Act



- **DECIDE**: Agents determine the best course of action
- Decision Trees
  - Level 1: Move or Stay
  - Level 2: Move Resources or Competition
  - Level 3: Move halfway or all the way



- **ACT**: Agents implement their chosen actions.
- Action Calculus:
  - Evaluate and execute decisions with varying costs and time horizons.
  - Navigate decision trees to identify optimal actions.
- Strategic Foresight:
  - Some agents anticipate future landscape changes and adjust actions accordingly.

Model Results

Baseline & Scenario Analysis

Baseline Parameter and Results

- Purpose:
  - Establish a standard for comparing agent performance across various scenarios.
- Setup:
  - Resource Availability: Balanced distribution between scarcity and abundance.
  - Initial Agent Capabilities: Normal distributions for each OODA component.
- Simulation Metrics:
  - Resource Management: How effectively agents manage and utilize resources.
  - Survival Rates: Number of agents that survive over time.
  - Decision-Making Effectiveness: Agents' ability to navigate the OODA loop and adapt to changes.
- Initial Findings:
  - Equilibrium: Agents reach a stable equilibrium within 200 iterations.
  - Agent Performance: Moderate agents perform best, showing highest average fitness outcomes.
  - OODA Scores: Critical ability for survival is effective sensemaking (Orient phase).

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

Scenario 1 and 2

Scenario 1: Low Resource Landscape

- Setup:
  - Resource Scarcity: Resources range from 0 to 25 units.
  - Increased Energy Loss: Move costs doubled from 1 to 2 resources.
- Objective: Test agent adaptability in a resource-constrained environment.
- Key Insights:
  - Only Smart and Moderate agents survive.
  - Survival Strategy: High observation and orientation capabilities are critical.
  - Behavior: Smart agents remain stationary, exploiting local resources; Moderate agents actively seek out resources.

Scenario 2: Low Resource Landscape with Global Knowledge

- Setup:
  - Expanded Observation Range: Agents can perceive a wider range (0 to 20 steps).
  - Resource Scarcity: Same as Scenario 1.
- Objective: Evaluate how enhanced global awareness affects decision-making and survival.
- Key Insights:
  - Smart agents dominate due to superior OODA capacities.
  - Survival Strategy: Smart agents use strategic patience, minimizing energy expenditure by accurately assessing the landscape.
  - Behavior: Moderate and Simple agents exhaust resources quickly by moving excessively.

Scenario 3 and 4

Scenario 3: Harsh World Smart Agents

- Setup:
  - High Cognitive Capabilities: Agents have maximum OODA scores.
  - Harsh Environment: Resource scarcity and high competition.
- Objective: Assess the cost and benefit of sophisticated decision-making in a challenging environment.
- Key Insights:
  - Outcome: All agents perish within a few hundred iterations.
  - Complexity Cost: High cognitive complexity leads to increased resource expenditure.
  - Survival Challenge: Strategic complexity is resource-intensive and unsustainable in a harsh environment.

Scenario 4: Harsh World Simple Agents

- Setup:
  - Low Cognitive Capabilities: Agents have minimal OODA scores.
  - Harsh Environment: Same resource scarcity and high competition as Scenario 3.
- Objective: Compare performance of simple vs. smart agents in the same environment.
- Key Insights:
  - Outcome: Similar performance to Smart agents, with low survival rates.
  - Reactive Behavior: Simple agents rely on spontaneous, reactive actions.
  - Resource Management: Both Smart and Simple agents struggle to manage resources effectively in a resource-poor environment.

Conclusions

- Key Findings:
  - OODA Loop Simulation: Demonstrates diverse cognitive capabilities' impact on agent fitness and survival.
  - Orient Phase: Crucial for sensemaking and effective decision-making.
- Future Work:
  - Extended Scenarios: Incorporate varying degrees of competition and dynamic resource landscapes.
  - Sensitivity Testing: Perform quasi-global sensitivity analysis to identify key model drivers.
  - Learning Mechanisms: Explore single and double-loop learning in different competitive contexts.

Questions?

References

- S. Frost, K. Goebel, and J. Celaya, “A Briefing on Metrics and Risks for Autonomous Decision-making in Aerospace Applications,” AIAA Infotech at Aerospace Conference and Exhibit 2012, 2012, doi: 10.2514/6.2012-2402.

Appendix: Model Results

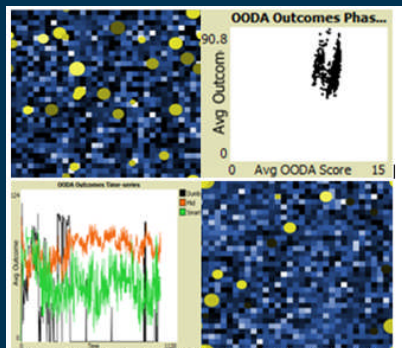


Figure 7. Baseline Environment, Time Series and Phase Portrait Plots.

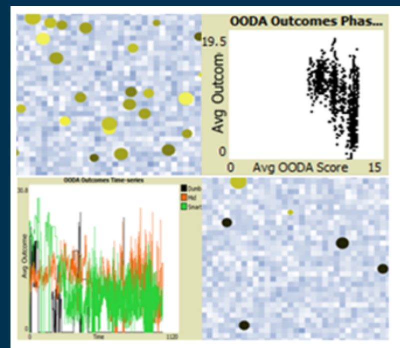


Figure 8. Scenario 1 Environment, Time Series and Phase Portrait Plots.

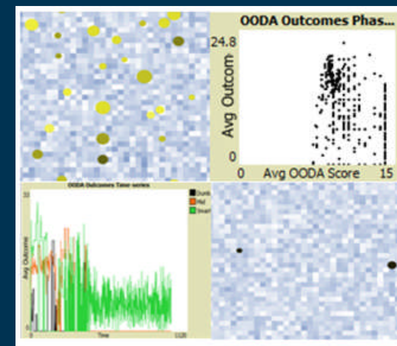


Figure 9. Scenario 2 Environment, Time Series and Phase Portrait Plots.

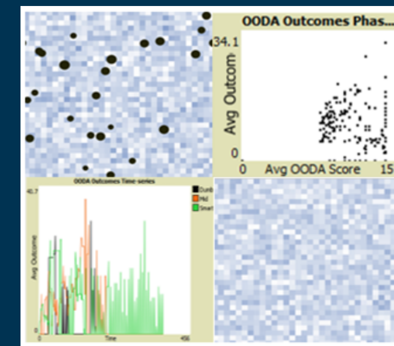


Figure 10. Scenario 3 Environment, Time Series and Phase Portrait Plots.

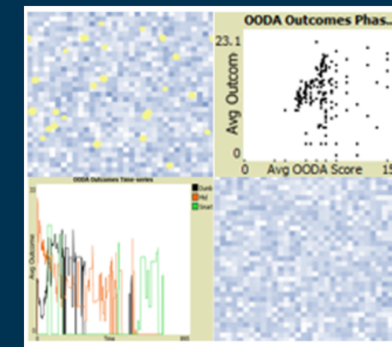


Figure 11. Scenario 4 Environment, Time Series and Phase Portrait Plots.

Baseline Results

Scenario 1:

Low Resource Landscape

Scenario 2:

Low Resource Landscape with Global Knowledge

Scenario 3:

Harsh World, Smart Agents

Scenario 4:

Harsh World, Simple Agents

Top Left: Initial Environment
Top Right: OODA Score, Outcome Phase Portrait
Bottom Left: OODA Score, Outcome Time Series Plot
Bottom Right: Final Environment