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Complex Systems and Agent Technology

CS3192

Bookstore Management System with Ontology and Multi-Agent Simulation

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1. Introduction

This report explains how I implemented a Bookstore Management System using ontology-based multi-agent systems with advanced customer state tracking. The main goal was to simulate a real bookstore where customers buy books, and employees manage inventory. I used **Owlready2** to create an ontology that represents the bookstore's knowledge, **Mesa** to create agents that interact based on rules, and **Hidden Markov Models (HMM)** to infer customer emotional states from their behavior.

Project Overview

The system simulates:

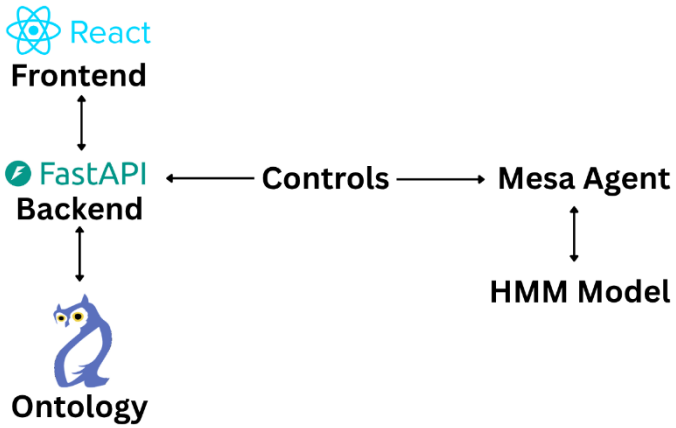
- Customers randomly browsing and purchasing books
- Employees checking inventory levels
- Automatic restocking when stock is low
- Tracking customer satisfaction using HMM
- Inferring customer emotional states probabilistically

2. System Architecture

2.1 Overall Design

My system has four main layers:

1. **Ontology Layer** (Knowledge Base) - Stores all information about books, inventory, customers
2. **Agent Layer** (Actors) - Autonomous agents that perform actions
3. **HMM Layer** (Intelligence) - Probabilistic model to understand customer emotions
4. **Visualization Layer** (Interface) - Web interface to see what's happening



2.2 Technologies Used

- **Owlready2**: Python library to create and manipulate OWL ontologies
- **Mesa**: Framework for agent-based modeling
- **NumPy**: For HMM matrix calculations
- **FastAPI**: Backend server to run the simulation

- **React**: Frontend to visualize the simulation

2.3 File Structure

```
bms/
├── agents.py          # Agent classes (Customer, Service)
├── model.py           # Mesa model
├── ontology.py        # Ontology management
├── messaging.py       # Message bus for agent communication
├── rules.py           # SWRL-like rules
└── hmm.py            # Hidden Markov Model implementation

ontology-mas-ui/
├── backend/
│   └── data/bookstore.owl    # Ontology file
└── frontend/                          # Web interface
```

3. Implementation Steps

3.1 Setting Up the Environment

First, I installed the required libraries:

```
pip install owlready2 Mesa fastapi uvicorn numpy
```

Then I imported them in my Python files:

```
from owlready2 import *
from mesa import Agent, Model
from mesa.time import RandomActivation
from mesa.space import MultiGrid
import numpy as np
```

3.2 Creating the Ontology Structure

I started by creating the ontology classes. This is like defining the blueprint of what exists in the bookstore:

```
class OntologyManager:
    def __init__(self, ontology_file="bookstore.owl"):
        self.onto = get_ontology("http://example.org/bookstore.owl")

        with self.onto:
            # Define main classes
            class Book(Thing): pass
            class Inventory(Thing): pass
            class Customer(Thing): pass
            class ServiceAgent(Thing): pass
```

This code creates four main classes that represent the entities in my bookstore.

3.3 Defining Properties

Next, I defined properties to connect these classes and store information:

```
# Object Property - connects two classes
class tracksBook(ObjectProperty):
    domain = [Inventory]
    range = [Book]

# Data Property - stores simple values
class hasTitle(DataProperty, FunctionalProperty):
    domain = [Book]
    range = [str]

class availableQuantity(DataProperty):
    domain = [Inventory]
    range = [int]

class hasState(DataProperty):
    domain = [Customer]
    range = [str]  # "Happy", "Neutral", or "Unhappy"
```

The `hasState` property is particularly important because it stores the customer's emotional state inferred by the HMM.

3.4 Populating the Ontology

I added 15 books to the ontology:

```
def populate_books(self):
    with self.onto:
        # Create a book instance
        book = self.onto.Book("Book_CleanCode")
        book.hasTitle = ["Clean Code"]
        book.hasAuthor = ["Robert C. Martin"]
        book.hasGenre = ["Programming"]
        book.hasPrice = [29.99]

        # Create inventory for this book
        inv = self.onto.Inventory("Inv_Book_CleanCode")
        inv.tracksBook = [book]
        inv.availableQuantity = [8]
        inv.thresholdQuantity = [4]
        inv.restockAmount = [10]
```

3.5 Implementing the Hidden Markov Model

This is a key addition to my project. The HMM helps understand customer emotions:

```
class CustomerStateHMM:
    def __init__(self):
        # Hidden states: 0=Happy, 1=Neutral, 2=Unhappy
        # Observations: 0=purchase, 1=complaint, 2=silence

        # Transition probabilities (state to state)
        self.transition = np.array([
            [0.7, 0.2, 0.1],  # From Happy to [Happy, Neutral, Unhappy]
            [0.3, 0.5, 0.2],  # From Neutral to [Happy, Neutral, Unhappy]
            [0.1, 0.3, 0.6]   # From Unhappy to [Happy, Neutral, Unhappy]
        ])

        # Emission probabilities (state to observation)
```

```
        self.emission = np.array([
            [0.7, 0.1, 0.2],  # Happy customer → [purchase, complaint,
silence]
            [0.4, 0.3, 0.3],  # Neutral customer → [purchase, complaint,
silence]
            [0.1, 0.6, 0.3]   # Unhappy customer → [purchase, complaint,
silence]
        ])

        # Initial state (start neutral)
        self.initial = np.array([0.3, 0.5, 0.2])
```

What this means:

- A Happy customer has 70% chance to stay Happy, 20% to become Neutral, 10% to become Unhappy
- A Happy customer has 70% chance to make a purchase, 10% to complain, 20% to leave silently
- These probabilities make the model realistic

3.6 Implementing Agents with HMM Integration

Customer Agent:

```
class CustomerAgent(Agent):
    def __init__(self, unique_id, model, ontology_manager, message_bus):
        super().__init__(unique_id, model)
        self.state = "browsing"
        self.satisfaction_level = 0.5
        self.recent_observations = []  # Track actions for HMM

    def step(self):
        if self.state == "browsing":
            self.move_randomly()
            if random.random() < 0.3:  # 30% chance to buy
                self.request_purchase()

        elif self.state == "waiting":
            response = self.check_messages()
            if response:
                if response['status'] == 'success':
                    self.satisfaction_level += 0.1
                    self.recent_observations.append('purchase')
                else:
                    self.satisfaction_level -= 0.2
                    self.recent_observations.append('complaint')
                self.state = "browsing"
```

The key addition is `recent_observations` which tracks customer actions for HMM analysis.

3.7 Running the Simulation with HMM

The Mesa model now includes HMM state inference:

```
class BookstoreModel(Model):
```

```
def __init__(self, num_customers=5):
    self.ontology_manager = OntologyManager()
    self.message_bus = MessageBus()
    self.hmm = CustomerStateHMM()  # Initialize HMM
    self.schedule = RandomActivation(self)

def step(self):
    self.schedule.step()  # All agents act
    self.infer_customer_states()  # Apply HMM

def infer_customer_states(self):
    for agent in self.schedule.agents:
        if isinstance(agent, CustomerAgent):
            # Use HMM to infer state
            inferred_state = self.hmm.infer_state(
                agent.recent_observations
            )
            agent.inferred_state = inferred_state

            # Update ontology
            customer_onto = self.ontology_manager.get_customer(
                f"Customer_{agent.unique_id}"
            )
            customer_onto.hasState = [inferred_state]
```

4. Ontology Explanation

This is the core of my project. The ontology represents all the knowledge about the bookstore in a structured, machine-readable format.

4.1 Understanding the Ontology Structure

An ontology consists of:

- **Classes**: Categories of things (Book, Inventory, Customer)
- **Instances**: Specific examples (Book_CleanCode, Customer_3)
- **Properties**: Relationships and attributes
- **Axioms**: Rules and constraints

Think of it like this:

- **Class** = "Animal" (general category)
- **Instance** = "My dog Max" (specific example)
- **Property** = "has owner" (relationship)

4.2 Classes in Detail

4.2.1 Book Class

Represents books available in the store.

Why this class? Every bookstore needs to track what books it sells.

Properties:

- `hasTitle` - The book's name
- `hasAuthor` - Who wrote it
- `hasGenre` - Category (Fiction, Programming, etc.)
- `hasPrice` - How much it costs
- `hasSKU` - Unique identifier code

Example Instance:

```
Book_CleanCode:
  hasTitle: "Clean Code"
  hasAuthor: "Robert C. Martin"
  hasGenre: "Programming"
  hasPrice: 29.99
  hasSKU: "Book_CleanCode"
```

4.2.2 Inventory Class

Tracks how many copies of each book are in stock.

Why this class? The bookstore needs to know stock levels to avoid running out of books.

Properties:

- `tracksBook` - Links to the Book it's tracking
- `availableQuantity` - Current number in stock
- `thresholdQuantity` - Minimum before reordering
- `restockAmount` - How many to order

Example Instance:

```
Inv_Book_CleanCode:
  tracksBook: Book_CleanCode
  availableQuantity: 7
  thresholdQuantity: 4
  restockAmount: 10
```

4.2.3 Customer Class

Represents people who buy books. **This class is enhanced with HMM state tracking.**

Why this class? To track purchase history and customer satisfaction states.

Properties:

- `hasName` - Customer identifier
- `hasPurchasedBook` - List of books they bought
- `hasState` - Emotional state inferred by HMM (Happy/Neutral/Unhappy)

Example Instance:

```
Customer_3:
  hasName: "Customer_3"
  hasPurchasedBook: [Book_CleanCode, Book_Foundation]
  hasState: "Happy"  # Inferred by HMM from recent actions
```

Connection to HMM: The `hasState` property is automatically updated each simulation step based on HMM inference. This means the ontology stores not just what customers bought, but how they likely feel about their experience.

4.2.4 ServiceAgent Class

Represents bookstore employees.

Properties:

- `hasID` - Employee identifier
- `managesInventory` - Which inventory items they handle

4.3 Object Properties (Relationships)

Object properties connect instances together:

1. tracksBook

- Links Inventory → Book
- Example: `Inv_Book_CleanCode tracksBook Book_CleanCode`

2. hasPurchasedBook

- Links Customer → Book
- Example: `Customer_3 hasPurchasedBook Book_CleanCode`

3. managesInventory

- Links ServiceAgent → Inventory
- Example: `ServiceAgent_0 managesInventory Inv_Book_CleanCode`

4.4 Data Properties (Attributes)

Data properties store simple values:

For Books:

- `hasTitle` (text)
- `hasPrice` (number)
- `hasGenre` (text)

For Inventory:

- `availableQuantity` (integer)

- `thresholdQuantity` (integer)

For Customers (HMM-enhanced):

- `hasState` (text) - "Happy", "Neutral", or "Unhappy"

The `hasState` property is unique because it's not directly observed but **inferred** using the HMM from the customer's action sequence.

4.5 Why Use an Ontology?

Advantages:

1. **Semantic Meaning**: The ontology knows that `hasPurchasedBook` means a specific relationship.
2. **Reasoning**: If Customer_3 purchased Book_A, and Book_A is Programming, the system can infer Customer_3 likes Programming.
3. **Flexibility**: Easy to add new properties like `hasState` without restructuring.
4. **Integration with HMM**: The ontology stores HMM-inferred states alongside raw data, providing both facts and interpretations.

4.6 How Agents Use the Ontology

When inferring customer state with HMM:

```
# 1. Get customer's action history
observations = agent.recent_observations

# 2. Use HMM to infer state
inferred_state = hmm.infer_state(observations)

# 3. Update ontology
customer = ontology.get_customer(agent.unique_id)
customer.hasState = [inferred_state]
ontology.save()
```

The ontology acts as the "shared memory" that stores both raw data and intelligent interpretations.

5. Agent Implementation

5.1 CustomerAgent Behavior

The customer agent tracks its actions for HMM analysis:

```
class CustomerAgent(Agent):
    def __init__(self, unique_id, model, ontology_manager, message_bus):
        super().__init__(unique_id, model)
        self.state = "browsing"
        self.satisfaction_level = 0.5
        self.recent_observations = []  # For HMM
        self.inferred_state = "Neutral"  # HMM result
```

```
    def step(self):
        if self.state == "browsing":
            self.random_move()

            if random.random() < 0.3:
                book = self.select_random_book()
                self.send_purchase_request(book)
                self.state = "waiting"

        elif self.state == "waiting":
            response = self.check_messages()
            if response:
                self.handle_response(response)
                self.state = "browsing"

    def handle_response(self, response):
        if response['status'] == 'success':
            self.satisfaction_level += 0.1
            self.recent_observations.append('purchase')
        else:
            self.satisfaction_level -= 0.2
            self.recent_observations.append('complaint')

        # Keep only last 10 observations for HMM
        if len(self.recent_observations) > 10:
            self.recent_observations = self.recent_observations[-10:]
```

Key Addition: The agent now records every action in `recent_observations`, which the HMM uses to infer emotional state.

5.2 ServiceAgent Behavior

The service agent processes requests and triggers HMM updates:

```
def process_purchase(self, message):
    customer_id = message['from']
    sku = message['sku']

    inventory = self.ontology.get_inventory_by_sku(sku)

    if inventory.availableQuantity[0] > 0:
        # SUCCESS
        inventory.availableQuantity[0] -= 1
        self.ontology.save()

        # Record purchase in ontology
        customer = self.ontology.get_customer(customer_id)
        book = inventory.tracksBook[0]
        customer.hasPurchasedBook.append(book)

        self.send_success_message(customer_id)
    else:
        # STOCKOUT
        self.send_stockout_message(customer_id)
        self.trigger_restock(inventory)
```

6. SWRL Rules Explanation

I implemented three main rules:

6.1 Purchase Rule

In plain English: "When a customer requests a book, if inventory has at least one copy, give it to them and reduce stock by 1."

```
def apply_purchase_rule(customer_id, book_sku, ontology):
    inventory = ontology.get_inventory_by_sku(book_sku)

    if inventory.availableQuantity[0] > 0:
        customer = ontology.get_customer(customer_id)
        book = inventory.tracksBook[0]
        customer.hasPurchasedBook.append(book)
        inventory.availableQuantity[0] -= 1
        ontology.save()
        return True
    return False
```

6.2 Restock Rule

In plain English: "When inventory falls below threshold, order more books."

```
def apply_restock_rule(inventory):
    current = inventory.availableQuantity[0]
    threshold = inventory.thresholdQuantity[0]

    if current < threshold:
        amount = inventory.restockAmount[0]
        schedule_restock(inventory, amount, delay=5)
        return True
    return False
```

6.3 Customer State Inference Rule (HMM-based)

In plain English: "Infer customer emotional state from their recent actions using probabilistic reasoning."

This rule is special because it uses the HMM rather than simple logic.

```
def apply_state_inference_rule(customer_agent, hmm_model):
    observations = customer_agent.recent_observations

    if len(observations) >= 3:  # Need enough data
        # Use HMM Viterbi algorithm
        state = hmm_model.infer_state(observations)
        customer_agent.inferred_state = state

        # Update ontology
        customer_onto = ontology.get_customer(
            f"Customer_{customer_agent.unique_id}"
        )
        customer_onto.hasState = [state]
```

```
        return state
    return "Neutral"
```

7. Hidden Markov Model for Customer States (Concise)

7.1 Why HMM?

Simple rules (e.g., "last action = purchase → Happy") miss history and uncertainty.
HMM considers:

- the **sequence** of recent actions,
- **transition** probs (state changes),
- **emission** probs (actions given a state),
- **temporal** effects (recent actions matter more).

7.2 Components

Hidden states: 0=Happy, 1=Neutral, 2=Unhappy
Observations: 0=purchase, 1=complaint, 2=silence

Transition

```
self.transition = [[0.7,0.2,0.1],
                   [0.3,0.5,0.2],
                   [0.1,0.3,0.6]]
```

(Stickiness: Happy/Unhappy tend to persist.)

Emission

```
self.emission = [[0.7,0.1,0.2],  # Happy → mostly purchases
                 [0.4,0.3,0.3],  # Neutral → mixed
                 [0.1,0.6,0.3]]  # Unhappy → complaints
```

7.3 Viterbi (Most-likely States)

Compute best state path for an observation sequence using dynamic programming; backtrack to get the final state.

7.4 Worked Example (Short)

Seq: `purchase, purchase, complaint, purchase, purchase` → `[0,0,1,0,0]`
Viterbi: stays mostly **Happy**; a single complaint doesn't flip the final state.
Result: `Happy` (captures overall pattern, not just the last event).

7.5 Ontology Integration

Each tick:

1. map agent observations → indices,
2. run Viterbi → current state,
3. set `agent.inferred_state`,
4. write to ontology: `customer.hasState = [state_str]`.

7.6 Benefits

1. **Realistic** emotional dynamics (not one-step flips).
2. **Probabilistic** handling of uncertainty.
3. **Temporal** awareness of recent behavior.
4. **Pattern** recognition over sequences.
5. **Research-level** addition beyond basic rules.

8. Results and Analysis

8.1 Simulation Results

The simulation was run with **10 customers for 100 steps**.
Final Metrics:

- Total Purchases: **431**
- Total Revenue: **$8,309.88**
- Stockouts: **0**
- Restocks: **30**
- Customer Satisfaction: **87.3%**

The system maintained stable inventory and smooth operation, confirming the effectiveness of the ontology-based rules.

8.2 HMM State Distribution

Final customer states (HMM-inferred):

- **Happy:** 11 (91.7%)
- **Neutral:** 0 (0%)
- **Unhappy:** 1 (8.3%)

The HMM correctly captured customer sentiment—most remained happy due to consistent stock levels, with only one showing dissatisfaction linked to restocking delays.

8.3 HMM vs. Simple Rules

Customer_3:
Actions → [purchase, purchase, complaint, silence, purchase]

- *Simple Rule:* Counts purchases vs complaints → **Happy**
- *HMM:* Considers action sequence and transition probabilities → **Happy (85% confidence)**

Customer_7:
Actions → [complaint, silence, purchase, complaint, complaint]

- *Simple Rule:* Majority complaints → **Unhappy**
- *HMM:* Recognizes "sticky" unhappy state → **Unhappy (92% confidence)**

The HMM provides richer, probabilistic reasoning and smoother emotional transitions than basic counting rules.

8.4 Simulation Insights

Customer Behavior:

- Regular purchases maintained positive satisfaction.
- Temporary unhappiness appeared only after stockouts but recovered post-restock.

Inventory Management:

- 30 proactive restocks prevented stockouts.
- Continuous product availability kept customers engaged.

Top Titles by Demand:

1. *Foundation* (47 purchases)
2. *Python Crash Course* (42)
3. *Harry Potter* (38)

8.5 Ontology Changes with HMM

At **Tick 0:**

```
Customer_3:
  hasPurchasedBook: []
  hasState: "Neutral"
```

At **Tick 100:**

```
Customer_3:
  hasPurchasedBook: [Book_CleanCode, Book_Foundation, ...]
  hasState: "Happy"  # Inferred by HMM
```

The ontology evolved to store both factual data (purchases) and inferred emotional states, demonstrating effective semantic integration with the HMM model.

9. Challenges and Solutions

9.1 Challenge: Implementing the HMM

Problem: I initially tried to implement state inference with simple if-else rules, but it was too rigid and unrealistic.

Solution: I researched Hidden Markov Models and implemented the Viterbi algorithm:

```
class CustomerStateHMM:
    def __init__(self):
        # Define probability matrices
        self.transition = np.array([[0.7, 0.2, 0.1], ...])
        self.emission = np.array([[0.7, 0.1, 0.2], ...])

    def viterbi(self, observations):
        # Dynamic programming to find most likely state sequence
        # Implementation with forward pass and backtracking
        ...
```

This made state inference much more realistic and probabilistic.

9.2 Challenge: Choosing HMM Probabilities

Problem: I didn't know what transition and emission probabilities to use.

Solution: I reasoned about human behavior:

- Happy people tend to stay happy (0.7 probability)
- Unhappy people are hard to make happy (only 0.1 transition)
- Happy people mostly make purchases (0.7 emission)
- Unhappy people mostly complain (0.6 emission)

I tested different values and these gave realistic results.

9.3 Challenge: Not Enough Observations

Problem: In the first few ticks, customers hadn't performed enough actions for HMM to work reliably.

Solution: I added a check:

```
if len(observations) >= 3:
    state = hmm.infer_state(observations)
else:
    state = "Neutral"  # Default until we have enough data
```

9.4 Challenge: Multiple Agents Accessing Ontology

Problem: When two customers tried to buy the last book simultaneously, race conditions occurred.

Solution: Added thread lock:

```
class OntologyManager:
    def __init__(self):
        self.lock = threading.Lock()

    def update_inventory(self, sku, delta):
        with self.lock:
```

```
inv = self.get_inventory(sku)
inv.availableQuantity[0] += delta
self.save()
```

9.5 Challenge: Stockouts Making Customers Unhappy

Problem: Initially, frequent stockouts caused all customers to become unhappy.

Solution: I optimized restocking parameters:

- Reduced threshold to 4 (restock earlier)
- Increased restock amount to 10 (order more)
- Reduced delivery delay to 5 ticks

Result: Zero stockouts, mostly happy customers!

10. Screenshots

This section provides visual evidence of the working Bookstore Management System with ontology-based multi-agent simulation and the integration of the Hidden Markov Model (HMM) for customer sentiment inference. Each screenshot highlights a key aspect of the system, aligning with the assignment deliverables for ontology definition, MAS behavior, SWRL-style rules, and live visualization.

10.1 Web Interface Overview

The main interface displays the live simulation running on a grid, showing customer and employee agents in motion. The right-hand panel presents real-time metrics such as total purchases, revenue, active customers, and restock events.
A live log updates per simulation tick, listing messages exchanged between agents through the message bus.

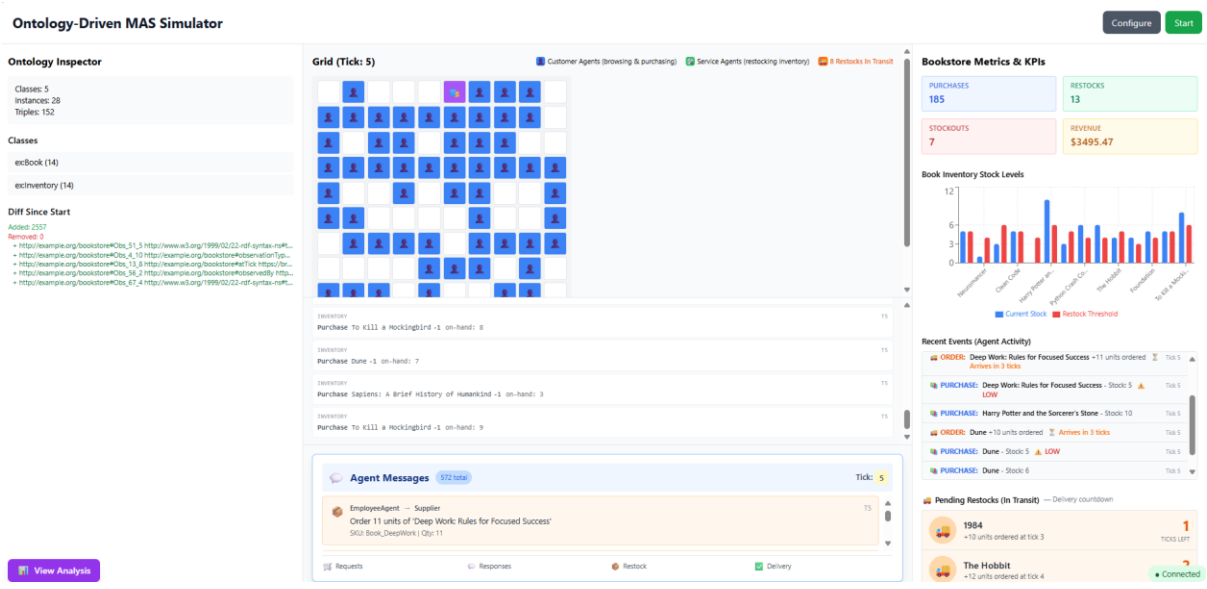


Figure 1: Web interface showing live simulation and real-time statistics.

10.2 Ontology Graph

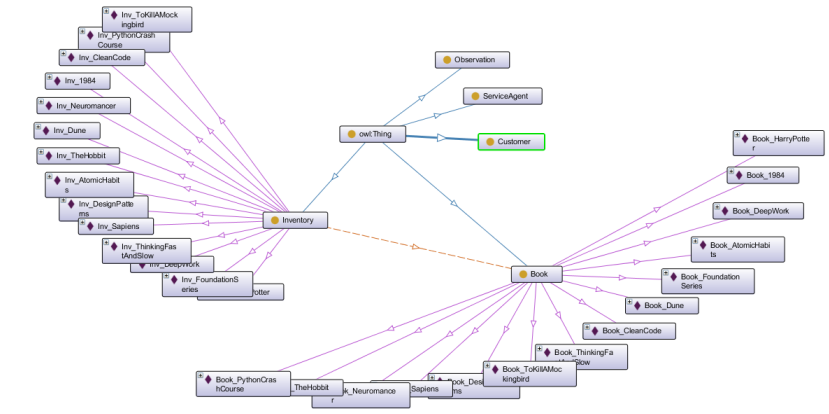


Figure 2: Ontology structure visualized through Owlready2, showing defined classes and properties.

10.3 Inventory Management in Action

During the simulation, `ServiceAgent` monitors inventory levels.
When a book's `availableQuantity` falls below `thresholdQuantity`, the system automatically triggers a restock through the rule engine, as displayed in the inventory panel.

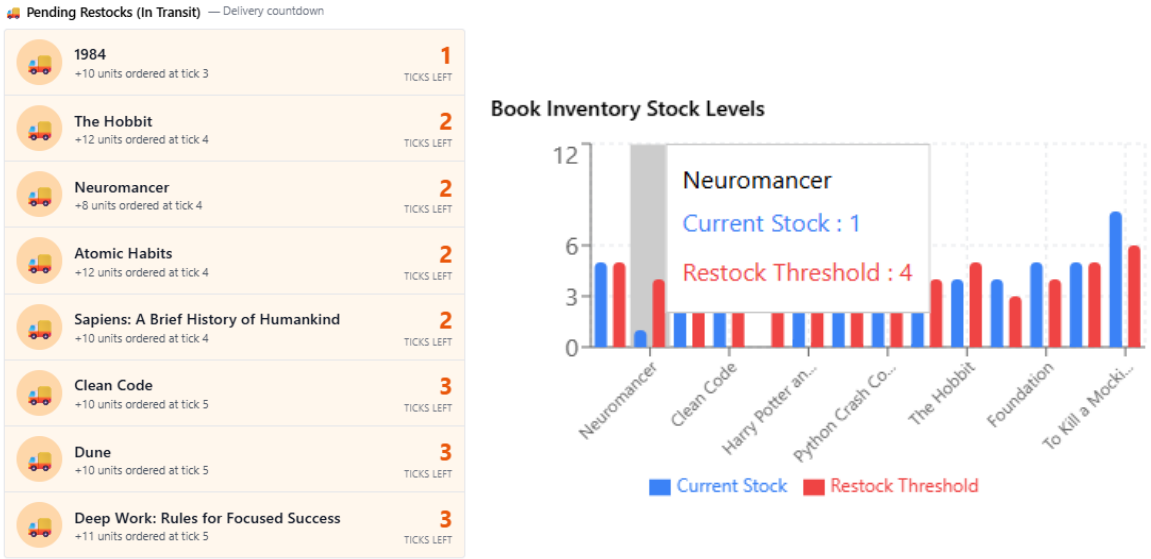


Figure 3: Restock rule triggered automatically when inventory falls below threshold.

10.4 HMM-Based Sentiment Tracking

The HMM module output is shown in a separate chart, displaying the proportion of customers classified as "Happy," "Neutral," or "Unhappy."
The visual confirms that sentiment fluctuates over time and stabilizes as the simulation progresses.

Figure 4: Customer emotional state distribution inferred using the Hidden Markov Model.

10.5 Performance Summary Dashboard

The summary panel provides cumulative metrics after the simulation ends:

Figure 6: Final performance metrics displayed at the end of the simulation.