

Emergent Consensus in Local-First Autonomous Agent Swarms

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Abstract

As Large Language Models (LLMs) evolve from simple chatbots to autonomous agents, the potential for simulating complex social dynamics increases exponentially. In this paper, I present EmotionSim, a local-first framework for running high-fidelity multi-agent simulations. Unlike cloud-based solutions that face latency and privacy hurdles, EmotionSim leverages quantized local models (specifically the Gemma 3 family) to execute rich, discrete-event simulations of disaster scenarios. I demonstrate the system's capabilities through an "Airplane Crash Investigation" scenario, where 10 diverse autonomous agents—ranging from a retired pilot to an investigative journalist—must autonomously perceive their environment, share information, and reach a consensus on the cause of the accident. My findings show that even small, locally-hosted models can exhibit sophisticated emergent cooperation and information propagation patterns, supported by a system throughput of over 200 tokens/second on consumer hardware.

Keywords: Multi-Agent Systems Autonomous Agents Emergent Behavior Local AI Disaster Simulation

1 Introduction

The field of Artificial Intelligence is undergoing a paradigm shift from static prompts to dynamic, agentic interactions. Researchers are increasingly interested in how swarms of AI agents can model complex human systems, from economic markets to social crises [1]. However, conducting this research often requires massive compute resources or reliance on expensive, opaque proprietary APIs.

I developed **EmotionSim** to democratize access to high-fidelity social simulation. By optimizing for local execution using the Ollama runtime and efficient discrete-event scheduling, EmotionSim allows researchers to "run a disaster in their terminal," observing the micro-dynamics of human cooperation and panic without data leaving their machine.

2 System Architecture

EmotionSim is built on a decoupled, event-driven architecture designed to balance narrative richness with simulation determinism.

2.1 Discrete Event Engine

At the core is a deterministic simulation engine. Unlike real-time game loops, the engine advances in discrete "ticks," allowing agents to deliberate for as long as necessary without desynchronizing the world state.

```
1 async def _execute_step(self):
2     # 1. Process pending world events (e.g., flood rising)
3     self._process_event_queue()
4
5     # 2. Agent Deliberation Cycle
6     actions = []
```

```

7     for agent in self.agents.values():
8         if agent.is_active:
9             # Agents make decisions based on local perception
10            action = await agent.tick(self.state)
11            actions.append(action)
12
13    # 3. Resolve Actions and Update World State
14    self._resolve_conflicts_and_apply(actions)

```

Listing 1: Deterministic Simulation Step

2.2 Rich Persona System

Agents are not merely prompt templates; they are stateful entities with defined psychological profiles. Each agent is initialized with Big Five personality traits, a specific skillset, and a hidden "backstory" that influences their perception.

```

1 class Persona(BaseModel):
2     name: str
3     occupation: str
4     # Big Five Traits (0.0 - 1.0)
5     openness: float
6     conscientiousness: float
7     extraversion: float
8     agreeableness: float
9     neuroticism: float
10
11    # Dynamic State
12    stress_level: int
13    health: int
14    inventory: List[str]

```

Listing 2: Persona Definition

This granularity ensures that a "Retired Pilot" agent notices engine debris that a "Civilian" agent would ignore, driving information asymmetry and the need for communication.

3 Experiment: Autonomous Investigation

To test the system's capacity for emergent logic, I designed the "Airplane Crash Investigation" scenario.

3.1 Scenario Setup

The simulation initializes 10 agents in a suburban neighborhood immediately following a light aircraft crash.

- **Agents:** Includes a Retired Pilot (witness), an ER Doctor (first responder), a Journalist (information broker), and several local residents.
- **Environment:** Locations include the Crash Site, a Hilltop vantage point, and a Community Center.
- **Information Distribution:** Key clues (e.g., "left engine smoke") are only visible to specific agents based on their location and backstory.

3.2 Emergent Behaviors

During the simulation, I observed distinct phases of autonomous behavior:

1. **Triage Phase (Steps 1-3):** High-empathy agents (Doctor, Pastor) immediately prioritized the "Crash Site" to help survivors, disregarding investigation.

2. **Information Consensus (Steps 4-7):** The Journalist agent actively moved between groups, aggregating witness reports. The Retired Pilot provided technical context to the Journalist’s questions.
3. **Conclusion (Steps 8+):** Without explicit instruction, the agents converged on a "mechanical failure" theory rather than "pilot error," synthesizing disjointed observations.

4 Benchmarks and Feasibility

While the primary focus is behavior, performance determines feasibility for large-scale research. I benchmarked the system using the ‘gemma3:270m’ model to test the limits of efficiency.

Table 1: Performance on Consumer Hardware (10 Agents)

Metric	Result
Total Duration (1 Step)	42.47 sec
Total Tokens Processed	12,549
Throughput	200.71 tokens/sec
Avg Agent Latency	4.72 sec

The system achieves over **200 tokens/second** throughput. This high efficiency implies that simulating complex social interactions is becoming accessible to individual researchers without the need for H100 clusters.

5 Conclusion

EmotionSim validates that local-first AI models have reached a threshold of capability sufficient for complex social simulation. By embedding these models in a robust discrete-event framework, I enable a new class of privacy-preserving, reproducible agentic research. Future work will focus on scaling to 100+ agents using hierarchical swarms.

Code Availability

The code is available at <https://github.com/jasperan/emotion-engine>.

References

- [1] Joon Sung Park, Joseph C. O’Brien, Carrie J. Cai, Meredith Ringel Morris, Percy Liang, and Michael S. Bernstein. Generative agents: Interactive simulacra of human behavior. *arXiv preprint arXiv:2304.03442*, 2023.
- [2] Zhiheng Xi, Wenxiang Chen, Xin Guo, Wei He, Yiwen Ding, Boyang Hong, Ming Zhang, et al. The rise and potential of large language model based agents: A survey. *arXiv preprint arXiv:2309.07864*, 2023.