Github Repo: https://github.com/Vaishya26/Stanford-Town-AI-Project

Project Report : CS 5660

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Abstract

Imagine a world where robots seamlessly blend into human society, carrying out daily routines and interacting with one another in believable ways. This is the vision behind Stanford Town, a virtual environment populated by AI agents that simulate human behavior. These agents are not mere automatons; they have personalities, memories, and the ability to form relationships. This project delves into the workings of Stanford Town, exploring the challenges and triumphs encountered in creating such a complex and realistic simulation. One key challenge lies in ensuring the agents' actions are believable. To address this, we utilize a sophisticated architecture that allows the agents to process information, formulate plans, and reflect on their experiences. This architecture draws inspiration from large language models, enabling the agents to communicate and engage with their environment in a natural way. The initial results are promising. The agents in Stanford Town exhibit individual behaviors that closely resemble those of real people. They go about their daily tasks, engage in social interactions, and even form emergent social structures. This demonstrates the potential for AI to create simulations that are not only realistic but also informative and engaging. As this project continues, we aim to further improve the believability of the agents and explore the implications of such advanced AI simulations. We envision a future where Stanford Town serves as a valuable tool for research and development across various disciplines, allowing us to gain deeper insights into human behavior and develop new technologies that benefit society as a whole.

1. Introduction

The primary objective of our project was to enable AI agents, computer programs designed for conversation, to engage in natural, unrestrained dialogues similar to human interactions. We aimed to overcome the challenge posed by conventional AI systems, which rely on fixed scripts or predefined patterns, limiting their ability to generate varied, human-like responses. These systems often struggle with comprehending deep conversations, adapting to topic changes, and maintaining a natural flow without sounding repetitive or off-topic.

In tackling this problem, we utilized diverse information to teach the AI agents the art of conversation. Our approach involved exposing them to different conversation examples, akin to teaching someone language through various dialogues. We equipped the AI with cognitive processes resembling human thinking and provided diverse conversation templates, similar to those employed in human chat.

The crucial aspect of our data was the amalgamation of conversation patterns, cognitive models, and memory structures. This mix of information served as the training material for the AI, empowering it to respond naturally and coherently in diverse conversational scenarios. This project aimed to bridge the gap in conversational AI, allowing for adaptive and dynamic interactions, akin to human conversations. The data strategy implemented for this project involved leveraging a vast corpus of actual OpenAI-generated data. This encompassed dialogues, text exchanges, and interactions sourced from OpenAI models, forums, and interactions with conversational interfaces powered by OpenAI's language models. The data was obtained via various mechanisms, including APIs and interactions with OpenAI's models, ensuring a diverse and comprehensive dataset. Rigorous validation techniques, comprising manual curation and automated verification, were employed to ensure data quality and alignment with our project's requirements. Additionally, the data collection process adhered to ethical guidelines, with a focus on user privacy and compliance with ethical standards established by OpenAI and relevant institutional review processes.

Today's conversational AI systems often fall short due to their rigid reliance on pre-written scripts. They lack the capacity to produce diverse, natural-sounding responses and struggle with understanding complex discussions and adapting to changing topics. The core issue lies in their inability to adapt on-the-fly, a fundamental aspect of human conversational dynamics. The innovation we pursued sought to address these limitations, pushing the boundaries of what AI can achieve in emulating human-like conversations.

2. Approach

Our team set out to create a lifelike simulation of a virtual town, Smallville, where 25 AI characters interact autonomously. To achieve this, we employed an innovative combination of advanced AI technology and custom-built systems.

The cornerstone of our project was the utilization of ChatGPT, a sophisticated language model. This model enabled the AI characters to engage in realistic conversations, make plans, form memories, and exhibit individual personalities. We leveraged ChatGPT's ability to comprehend and generate human-like language to enhance the believability of the AI characters' behavior.

Additionally, we developed a framework that provided these AI characters with simulated minds—complete with memories and experiences. This system allowed the AI agents to recall past events, plan future actions, and interact meaningfully within the virtual environment. Through this framework, the AI characters were designed to perceive and react to the world in a way that closely resembled human behavior.

Our unique approach also encompassed the incorporation of interactive elements for human users. These users could step into Smallville as either existing AI characters or newcomers. Moreover, they had the capability to influence the AI characters by conversing with them naturally or by issuing instructions via an "inner voice."

By combining these fancy language skills with our special thinking system and allowing people to join in, we made a really unique and lifelike virtual world. In this world, AI characters and people could chat, make friends, and do all sorts of things together.

Our primary goal was to comprehensively understand the inner workings of a simulated RPG-style virtual world populated by 25 AI-controlled agents. This world, akin to The Sims, was detailed in a research paper authored by a team from Stanford University and Google.

To achieve this understanding, we embarked on a detailed exploration of the backend architecture driving this virtual world. It involved dissecting the intricate interplay between various elements shaping the agents' behavior. This included an in-depth examination of the memory structures and cognitive modules that formed the backbone of the AI agents' decision-making processes.

Within the memory structures, we uncovered three essential components: spatial, associative, and scratch memory. Spatial memory seemed responsible for the agents' perception of their environment, associative memory facilitated the connections between disparate pieces of information, and scratch memory played a crucial role in temporary data storage and quick retrieval.

Further exploration into the cognitive modules revealed a nuanced understanding of each module's role. The perceived module processed sensory input, retrieved facilitated memory recall, plan orchestrated future actions, reflected allowed introspection, executed managed task completion, and converse generated interactive dialogue.

Moreover, we gained insights into the process of generating responses by interfacing with the OpenAI server. This exploration provided a comprehensive understanding of how the AI agents interacted based on prompts and how these interactions were facilitated through API calls to an external server, leveraging language models like ChatGPT.

Our efforts went beyond mere replication; instead, we aimed to decipher the complex backend systems orchestrating the agents' behavior within this simulated world. From understanding memory structures guiding behavior to grasping the cognitive modules orchestrating agent actions and their interaction with an external AI server, our objective was to comprehend the intricate workings of this fascinating environment.

3. Experiments and Results

3.1. Initialization and Simulation Setup

Initially, we began by setting up the simulation environment in reverie.py. We faced issues loading the simulation data and configuring the server properly. Experimentation: Through debugging and several iterations, we managed to load the necessary data and set up the server to control the simulation flow effectively. This allowed us to establish an interaction interface for users to control and observe the simulation.

3.2. Persona Representation and Behavior

Debugging and Exploration: Upon initializing the simulation, we integrated the Persona class from persona.py to define agents' behaviors. Initially, there were challenges in setting up the personas' memory structures and cognitive modules correctly.

Experimentation: We debugged issues related to the initialization of memory structures and modules. By trial and error, we configured the Persona class methods to control how agents perceive their environment, make decisions, and manage their internal states effectively.

3.3. Perception, Memory, and Decision-making

Trial, Error, and Iteration: As we moved to handle perception, memory, and decision-making in perceive.py and retrieve.py, we encountered challenges in managing the personas' perception mechanisms and retrieving relevant information from memory.

Refinement through Experimentation: By iteratively tweaking the code and closely observing how personas perceived their environment and retrieved information, we refined the perception and retrieval processes. We adjusted the scripts to better handle the agents' decision-making based on their perceptions and memories.

3.4. Reflection and Thought Generation

Debugging for Reflection: When attempting to simulate reflective processes in reflect.py, we encountered issues generating insightful thoughts and actions based on the personas' experiences.

Experimentation for Improvement: Through multiple debug sessions and iterative experiments, we enhanced the reflective mechanisms. We refined the code to use recent experiences, thoughts, and interactions effectively, generating more meaningful reflections for the agents.

3.5. Execution of Plans and Actions

Debugging Execution Flow: Moving to handle the execution of plans and actions in execute.py, we faced challenges in correctly navigating the personas within the environment and executing actions based on plans.

Iterative Testing and Refinement: We iterated on the pathfinding algorithms and action execution logic, debugging issues related to movement, interaction, and pathfinding. By testing different approaches, we improved the execution of plans within the simulation.

3.6. Conversation and Dialogue Generation

Debugging for Conversations: Finally, while dealing with agent-to-agent interactions and conversations in converse.py, we encountered difficulties generating coherent dialogues and managing conversational contexts.

Refinement through Trial and Error: Through multiple rounds of trial and error, we refined the conversation generation code. We experimented with various dialogue generation strategies, summaries, and inner thoughts to create more realistic interactions between agents.

Throughout this experimental process, each step involved debugging, trial, and refinement, gradually improving the simulation's functionality and achieving the desired outcome of creating a more nuanced and realistic simulated environment for the agents.

3.7. Failure

Our experimentation with the simulation environment primarily aimed to observe and enhance the interactions and behaviors of AI-driven agents, mimicking human-like activities. However, due to token limitations within the OpenAI API, we encountered initial constraints in obtaining detailed conversational responses from the agents. These limitations led us to gain insights into the agents' communication styles, albeit with a restricted token size, allowing us to understand their initial interactions and engagement patterns.

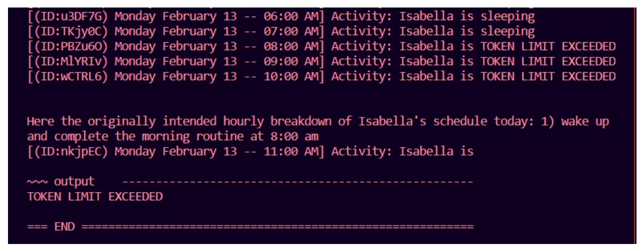

Figure 1. Token limit exceeded

3.8. Results

Progressing through iterative steps, we observed significant developments in the agents' knowledge acquisition and actions. For instance, during the simulation, an event unfolded where Isabella, one of the agents, initiated and hosted a Valentine's party. This event triggered a cascade of interactions as multiple agents within the simulation began seeking and arranging dates for the party. This instance highlighted the emergent behavior within the simulated world, showcasing how agents responded dynamically to events initiated by their peers, reflecting social behaviors akin to real-life scenarios.

Figure 2. Isabella schedule

However, a notable challenge arose as we were unable to witness the simulation in real-time due to our limited access, confined to monitoring the simulation's progress solely through the terminal interface. Nevertheless, leveraging pre-stored simulation data, we were able to visualize and analyze comprehensive aspects of the agents' states, actual conversations, and upcoming tasks. By exploring these stored simulation snapshots, we gained valuable insights into the agents' ongoing activities, interactions, and future plans, enabling a deeper understanding of their evolving dynamics.

Furthermore, to expedite our analysis and exploration of the simulation, we augmented the simulation speed, allowing us to progress further through the agents' experiences, interactions, and changes in their environment. This acceleration facilitated a broader observation of how agents' behaviors evolved over time and how various events and actions influenced their decision-making processes and social engagements.

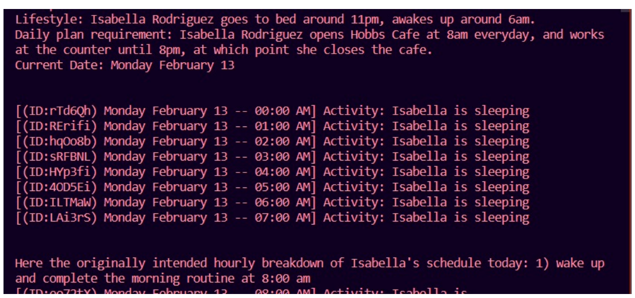

Figure 3. Isabella sleep schedule

In summary, while initial limitations posed challenges in obtaining detailed real-time insights, our step-by-step progression through the simulation enabled us to grasp the emergent behaviors, social interactions, and evolving dynamics among the AI-driven agents. Through iterative adjustments and leveraging pre-stored data, we gained valuable qualitative insights into their behaviors, actions, and responses to events within the simulated world, shedding light on the complex nature of human-like interactions within an AI-driven environment.

4. Scenario Explanation

4.1. Party Planning

Isabella Rodriguez announces her plan to host a Valentine's Day party at Hobbs Cafe.

The party is scheduled for February 14th from 5 pm to 7 pm.

4.2. Agent Awareness

Agents, such as Giorgio, Sam, Jennifer, Eddy, Ayesha, John, Maria, Klaus, Wolfgang, Tom, Latoya, and Abigail, are aware of the party.

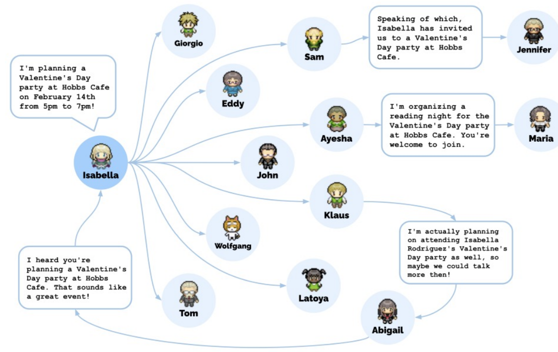

Figure 4. Agent conversation architecture

Each agent seems to have received information about the event, either directly from Isabella or through other agents.

4.3. Communication and Interaction

The text mentions a "diffusion path," indicating how information about the party has spread among the agents.

The agents, upon learning about the party, engage in related conversations, expressing their reactions and plans.

4.4. Memory Stream and Retrieval

The scenario involves the memory stream, comprising observations such as Isabella's activities and the state of objects (e.g., desk, bed, refrigerator) in the virtual world.

Retrieval is described as identifying a subset of relevant observations to pass to the language model to influence its response.

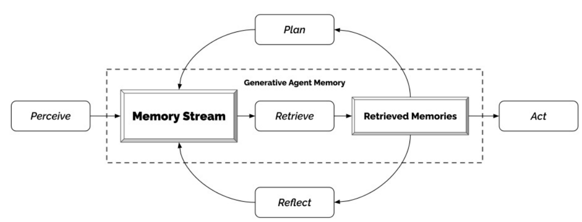

Figure 5. Memory architecture

5. Work Division

5.1. Contribution by each team member

The following table showcases the efforts put in by each team member. It also describes about the contributed aspects of the project and its implementation details.

Student Name	Contributed Aspects	Details
Arpit Vaishya	AI Decision-Making and Behavior Planning	Explored how AI characters make decisions and plan actions. Analyzed behavior planning in the agent lifecycle.
Yash Jain	Memory Implementation and Experience Usage	Explored the memory structure within AI agents. Investigated how agents use past experiences for actions.
Yash Shah	Character Interactions and Social Dynamics	Explored AI character interactions and social dynamics. Analyzed how AI characters engage and interact.
Sidharth Singh	Prompt Generation and AI Character Attributes	Explored prompt generation and character attributes. Analyzed structure and generation of AI character prompts.

Table 1. Contributions of team members.

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