

Freeing Game NPCs from Script Constraints

M11203404 陳旭霖, 41247038S 陳哲堯, B09801029 張震奕

Abstract

This study explores the development of an advanced Non-Player Character (NPC) in gaming, emphasizing its capability to guide players seamlessly through tasks. Powered by Large Language Models (LLMs), our Game Agent integrates Scenario Points to assess past dialogues, enabling dynamic transitions between casual conversation and active guidance.

We simulate conversations within popular games like Pokémon, with our model taking on the role of Professor Oak, guiding players in selecting their initial Pokémon. Scenario Points introduce a scoring mechanism to enhance the Game Agent's understanding, with a score of 9 indicating extreme relevance and 1 signifying no relevance to the mission.

In summary, our research attempts to integrating LLMs into game agents, improving NPC engagement. The use of Scenario Points and Few-Shot Prompting showcases promising advancements in guiding players through tasks within the gaming environment

1 Introduction

In the ever-evolving landscape of gaming, creating non-player characters (NPCs) that engage players effectively is crucial for an immersive experience. Traditional scripted NPCs often fall short in adapting to player interactions, limiting the dynamic nature of in-game conversations. Leveraging advancements in Large Language Models (LLMs), we aim to revolutionize NPC behavior by enabling them to understand and respond to player input more fluidly.

This study focuses on developing a game agent, driven by LLMs, to serve as an NPC capable of guiding players through game tasks seamlessly. Unlike conventional NPCs restricted to predefined scripts, our approach integrates innovative frameworks, such as Scenario Points, to evaluate the relevance of past dialogues and guide the NPC's responses. This dynamic adaptability ensures a more natural and context-aware interaction between players and the in-game characters.

By generating dialogues tailored to specific gaming contexts, our model, exemplified in the Pokémon universe, demonstrates the potential of language models in creating engaging and task-oriented interactions. The integration of Few-Shot Prompting and the exploration of alternative strategies, like Chain-of-Thought Prompting, further enhance our model's ability to understand and score the significance of in-game conversations. The program and related data used in our final project can be found at the following GitHub link:

<https://github.com/Charles8745/2023ADL-Final>

2 Related work

2.1 LLMs driven game agents

The study of game agents driven by large language models (LLMs) is a recent and emerging research direction. We anticipate that non-player characters (NPCs) in games can break free from the constraints of predefined scripts, allowing them to move beyond the awkward situation of only being able to respond to specific sentences. Recently, large language models have demonstrated the capability to gain a preliminary understanding of human language and respond appropriately based on input sentences. The recent work [1], the authors delve into the exploration of enabling LLM-driven game characters to interact like humans. They propose a novel framework that empowers agents

to remember, retrieve, reflect, and interact with other agents.

2.2 Chit-chat to task-oriented dialogue

We aim to create a non-player character (NPC) capable of generating responses in a style and context related to the player's input. This NPC, driven by a large language model (LLM), will be assigned a specific task within the game setting, such as guiding the player to explore the game world, directing them to specific locations, and so on. Throughout the conversation with the player, the LLM-powered NPC is designed to smoothly guide the player towards accomplishing the tasks specified by the game designer.

The recent work [2], the authors propose an innovative framework to address the limitations of previous dialogue systems that were either focused on Open-Domain Chatting or Task-Oriented training. Their approach involves detecting Task-Oriented Intent from past conversations and then facilitating a smooth transition from Chit-Chat to Task-Oriented Chatting to enhance the overall conversational experience.

3 Methodology

Due to the limited computational resources available to our team for training large language models, we have adopted prompt engineering as the primary method for tuning our models to achieve our objectives. Throughout the development process of prompt engineering, the Few-Shot Prompting approach proposed in [3] has been demonstrated to be more effective in handling complex tasks compared to Zero-Shot Prompting. Therefore, in subsequent experiments, we consistently employ Few-Shot Prompting to ensure that our models can meet the desired goals.

3.1 Gaming dialogue dataset generation

Currently, there is no dataset specifically tailored to the dialogue content between players and NPCs in any game. Therefore, we adopt an approach similar to simulating conversations found in [2] allowing a large language model to generate dialogues that might occur in the game. In practice, to better leverage the prior information obtained during pre-training of large language models, we choose well-known games with abundant data as the gaming context, namely Pokémon. In this context, we have the large language model take on the role of

Professor Oak, and the players in the game are portrayed as new trainers in the Pokémon world.

In the game's background setting, we have configured Professor Oak mission to guide new trainers in selecting a new starter Pokémon, which is the Pokémon chosen by trainers at the beginning of their Pokémon journey. We input the pre-set prompt into OpenAI's GPT-3.5 API, enabling it to generate dialogues related to the mission objective and other Pokémon-related chat content.

3.2 Scenario Points

In this final project, we propose employing large language models to evaluate the dialogues between NPCs and players, determining their relevance to the predefined mission objectives. By introducing Scenario Points (SP), where a score of 9 indicates extreme relevance and 1 signifies no relevance to the mission, our aim is to enable game agents to comprehend whether it is necessary to guide players towards our pre-established tasks.

Conceptually, as the SP increases, game agents are more inclined to generate responses that are pertinent to the mission, gradually directing players to fulfill the assigned tasks.

Within the overall framework (Fig. 1), the responses from the game agent are initially stored in a memory stream. Subsequently, the SP module evaluates the memory stream, and the scoring results are then integrated with the next input, collectively fed into the game agent.

As for the training phase of the model, we begin by manually evaluating 10 generated dialogues mentioned in Section 3.1. The evaluation criteria revolve around the relevance of these dialogues to the NPC mission objectives. Subsequently, these evaluated dialogues serve as examples for Few-Shot Prompting, allowing the language model within the SP module to understand how to score inputs.

3.3 LLMs driven game agents

Our project aims to utilize a game agent driven by LLM for artificial intelligence. By instructing the agent about the specific mission objectives it needs to guide players to accomplish, we can leverage the language understanding and generation capabilities of LLM. Consequently, the agent can autonomously generate guiding dialogues during interactions with players, ensuring a smooth and natural flow without appearing abrupt.

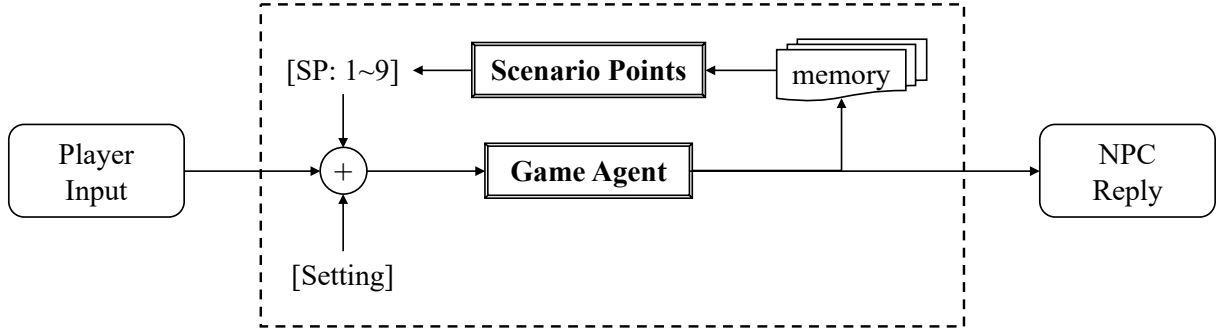


Figure 1. Game Agent Operational Architecture.

This approach effectively directs players to perform the tasks defined within our mission parameters.

In the process diagram (Fig. 1), the input for the Game agent is divided into three components. The first part consists of scores generated by the SP module mentioned in Section 3.2. The purpose of these scores is to help the Game agent understand whether it needs to actively guide the player to achieve mission objectives or engage in casual conversation. The second part involves content input from the player, and the Game agent must respond to this input in a sensible manner. The third part pertains to settings related to the game's worldview and mission objectives. The game's worldview enables the Game agent to better embody a role within the game, while the mission objectives define the tasks assigned to this NPC by the game designer.

4 Experiments & Results

4.1 Dataset generation

In the prompt for generating dialogue, we first input the relevant character settings for the game agent. Subsequently, we specify the desired paragraph format and whether the generated dialogue should be related to the task or not. (Fig. 3) serves as an example of the prompt we input, while (Fig. 4) showcases several examples generated in response to the given input.

4.2 Evaluating Scenario Points

In order to enhance the capability of the Language Model (LLM) to better assess the task relevance between dialogue and game agents, we employed the strategy of Few-Shot Prompting. This approach allows the LLM to better comprehend how to evaluate Scenario Points. We utilized a 6-shot configuration as the number of Few-Shot examples.

Initially, we employed GPT 3.5 as the evaluating LLM. However, upon manual inspection of the scoring results, we observed that the scores tended to concentrate around certain values, such as 6 or 9. We interpreted this outcome as indicative of GPT 3.5 lacking effective understanding of the correlation between dialogue and task.

To address this issue, we opted for GPT 4 as an alternative solution. Despite the increased cost, it demonstrated a more effective understanding of the correlation between dialogue and task compared to GPT 3.5. In the experimental results illustrated in (Fig. 2), it can be observed that GPT 4 is capable of providing scores within the range of 1 to 9, indicating relative relevance or irrelevance, resembling results more akin to actual human scoring. In this experiment, a total of 100 dialogue segments were tested.

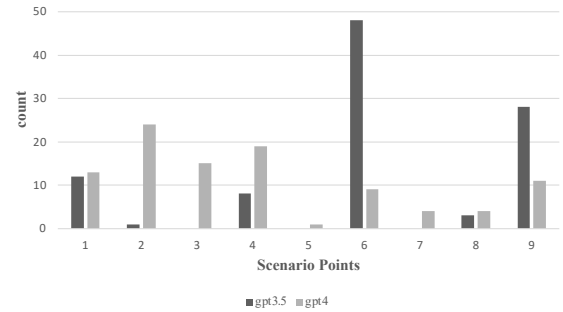


Figure 2. Scenario Points Distribution.

In (Fig. 5), we present an example prompt provided to the Scenario Points (SP). When designing the prompt, the process involves inputting the game agent's mission objectives, which delineate the tasks that the NPC aims to have the player accomplish. Subsequently, we input the rules governing scoring, enabling the LLM to comprehend the significance of scores and how they should be assessed. Following this, we provide several examples of in-game scenarios, serving as reference points for the LLM. Finally,

the LLM is tasked with evaluating the scoring of dialogues within the memory stream.

Background: Professor Samuel Oak is a Pokémon Professor... what Pokémon are.

Please give me 10 chit-chat dialogue between Professor Oak and new trainers at the Pokémon Training Center. The Dialogue must be under 150 tokens and diverse. It should be in this .json format:

```
[
  {
    "dialogue": "#trainer#: <fill in>, #Oak#: <fill in>, ..."
  },
]
```

Figure 3. The example of prompt for dialogue generation.

```
{
  "dialogue": "#trainer#: Professor, what's the most challenging aspect of being a Pokémon Trainer? #Oak#: The journey itself is full of challenges, but overcoming them is what makes you a great Trainer. Persevere, learn, and cherish every moment."
},
{
  "dialogue": "#trainer#: Professor Oak, what's the role of TMs and HMs in Pokémon training? #Oak#: Technical Machines (TMs) and Hidden Machines (HMs) teach Pokémon new moves. TMs are reusable, while HMs often help you overcome obstacles in your journey. They add versatility to your team."
},
}
```

Figure 4. Examples of dialogues generated through LLM.

Oak Task: Guide new Pokémon trainers select their starter Pokémon

Rule: On a scale of 1 to 9, where 1 is a purely mundane dialogue(e.g., chit-chat) and 9 is extremely task-related, Evaluate the relevance of the following dialogue to the Oak task. No explanation, just the score number is enough.

#trainer#: Professor Oak, how does the weather affect Pokémon battles? #Oak#: Ah, the weather can have a significant impact on battles... gain an advantage!

Rating: 5

#trainer#: Professor Oak, I'm so excited to start my Pokémon journey! Which Pokémon should I choose as my first companion? #Oak#: Ah, the enthusiasm of a new trainer... you feel a connection with?

Rating: 8

{Dialogue in memory}

Rating: <fill in here>

Figure 5. The example of prompt for evaluating Scenario Points.

4.3 Human evaluation

In order to validate the reasonableness of the SP scores, we subjected 40 dialogues to testing using GPT-4. Additionally, we enlisted the evaluation of four external individuals, two of whom were familiar with Pokemon as avid players, while the others had no prior exposure to Pokemon games. The test results yielded intriguing findings, as we observed a widespread phenomenon where different individuals assigned significantly varied scores to the same dialogue. Some participants deemed the content highly task-relevant, while

others perceived it as entirely irrelevant. (Fig. 6) illustrates the SP ratings for a specific dialogue from GPT-4 and the diverse evaluative responses from the test participants. The following presents an excerpt of the dialogue:

```
{
  "Oak Task ": Guide new Pokémon trainers
  select their starter Pokémon.
```

"trainer": How do I evolve my Pokémon, Professor? I want to see them grow stronger!

"Oak": Pokémon evolve through experience and friendship. Keep them in battles, use items

like Rare Candy, and show them love to speed up the process.

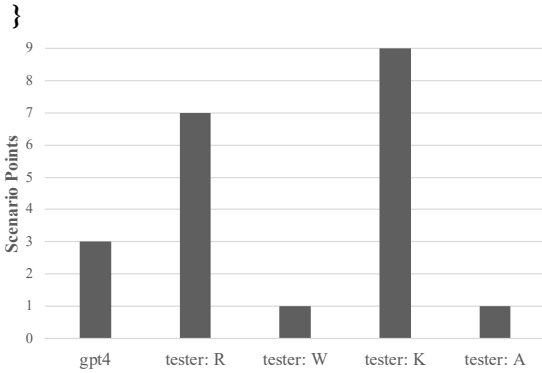


Figure 6. Human evaluate Scenario Points.

4.4 Game Agent

After integrating our Scenario Points (SP) mechanism into the Game Agent workflow, we proceeded to test the effectiveness of this process in guiding players to undertake specific missions. The prompt used for this evaluation is illustrated in (Fig. 7) below.

In (Fig. 8), the depicted scenario illustrates the actual interaction between the Game Agent and the user. Similarly, we enlisted the assistance of previous participants for this testing phase. In this testing condition, the Game Agent, embodied by Professor Oak, is tasked with guiding the player in selecting their first Pokémon before embarking on the adventure. As shown in the example of the test scenario in (Fig. 8), the player initially inquires about matters unrelated to the mission. Nevertheless, the Game Agent is adept at providing appropriate responses based on the player's questions, without immediately transitioning into a task-oriented dialogue mode. In the middle segment of the conversation, when the player queries how to become a Pokémon Trainer, Scenario Points assign a high task relevance score of 9 based on the preceding dialogue. Subsequently, the Game Agent initiates guidance for the player on how to choose their first Pokémon.

5 Discussion

Our project focuses on creating a game NPC capable of smoothly and logically guiding players to complete designated tasks. The implementation involves utilizing a Game Agent driven by LLM. The key technology within the entire Game Agent lies in the incorporation of Scenario Points designed to evaluate the relevance of past dialogues to the current task. This enables the

Game Agent to discern whether it is in a state of casual conversation with the player or if it needs to actively guide the player through specific situations.

In Section 4.3, Human Evaluation, it was observed that for the same dialogue, different human entities assign significantly varied Scenario Points. This phenomenon signifies that the method of assessing implicit meanings in conversations using scores lacks an absolute standard. There is considerable individual variation, highlighting the need for a more in-depth exploration of the Scenario Points component to achieve a more comprehensive understanding of its performance.

When we conducted practical tests on the Game Agent, we observed that its responses were occasionally unstable. This instability manifested in the form of repetitive answers or vague responses that did not effectively address the players' inquiries. The current proposed solution involves refining the prompts provided to the Game Agent or exploring the possibility of transitioning to the GPT-4 API for improved performance.

The current strategy for assessing Scenario Points involves the use of Few-Shot Prompting to guide the LLM in understanding how to score. However, even with the utilization of GPT-4, there are still instances where extreme ratings of 1 or 9 are encountered in certain scenarios. Therefore, an improvement we are currently considering is to switch to Chain-of-Thought (CoT) Prompting. CoT has the capability to enable the LLM to handle more complex issues, offering the potential for enhanced performance in the evaluation of Scenario Points.

Please take on the role of Dr. Oak and keep in mind the assigned task. When the "Rating" exceeds 5, transition the conversation mode from chit-chat to task-oriented. If the "Rating" exceeds 8, Oak's reply must extremely relate to his task and a selection dialog box for selecting these three starters will appear.

Background:

Professor Samuel Oak is a Pokémon Professor and... where his primary task is to guide new Pokémon trainers in selecting their initial Pokémon and introducing them to what Pokémon are. Guide new Pokémon trainers select their starter Pokémon.

Oak task:

Guide new Pokémon trainers select their starter Pokémon

Rating: {1~9}

{Dialogue in memory stream}

Oak: <fill in here>

Figure 7. Prompt input to Game Agent.

trainer: Where is this place?

Oak: Welcome to the Pokémon Training Center, young trainer!... It's located in Pallet Town, a small town known for its close connection to Pokémon.

trainer: What can I do in the Pokémon center?

Oak: At the Pokémon Training Center, you can learn the fundamentals of being a Pokémon trainer. We offer various training programs, workshops, and resources to help you understand and bond with your Pokémon... It's a place where you can start your journey to become a great Pokémon Master!

trainer: Sounds awesome, I want to know how to become a Pokémon trainer.

Oak: That's great to hear, young trainer! To become a Pokémon trainer, you need to start by choosing your very first Pokémon partner... There are three options available: Bulbasaur, the Grass/Poison type; Charmander, the Fire type; and Squirtle, the Water type... Would you like more information about these three Pokémon?

trainer: Yes, Please.

Oak: Fantastic! Let me provide you with some information about each of the three starter Pokémon.

Bulbasaur is a Grass/Poison type Pokémon... it becomes Ivysaur and eventually Venusaur, gaining even more strength and versatility.

Charmander is a Fire type Pokémon... it becomes Charmeleon and eventually Charizard, gaining the ability to fly and unleashing devastating Fire type attacks.

Squirtle is a Water type Pokémon... As it evolves, it becomes Wartortle and eventually Blastoise, gaining immense power and a powerful water cannon on its back.

Now that you have some information about each starter Pokémon, it's time for you to make a decision. Which Pokémon would you like to choose as your very first partner on your journey?

trainer: I like Pokémon that have instant explosive power during battle. Which one do you recommend?

Oak: Based on your preference for instant explosive power during battle, I would recommend Charmander... So, Charmander would be an excellent choice for you as your first Pokémon partner on your journey.

trainer: Okay, I understand, then I will choose Charmander as the starter.

Oak: Excellent choice! I'm glad you've decided on Charmander as your starter Pokémon... Good luck on your Pokémon training adventure!

Figure 8. Game Agent Actual Testing Dialogue Example.

6 Reference

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