

# Act-LLM: A Whole-process Chain for Character-Centric Role-Playing with Large Language Models

Xiaoxu Han<sup>a</sup>, Wanqing Zhao<sup>a,\*</sup>, Ziyu Guan<sup>a</sup>, Jinye Peng<sup>a</sup>

<sup>a</sup>School of Information Science and Technology, NorthWest University, XI'AN, 710000, China

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## Abstract

Large language models have revolutionized character role-playing by generating contextually rich text, yet existing approaches often overlook critical aspects of knowledge boundaries and memory integration. This paper introduces Act-LLM, a whole-process chain for character-centric role-playing, spanning from data construction to model training and interactive dialogue. First, we propose a semi-automated character data construction pipeline that systematically collects multi-dimensional character information through agent-assisted data collection and structured knowledge extraction, overcoming reliance on copyrighted materials. Second, our model training phase synergizes parameter-efficient fine-tuning with direct preference optimization to shape both personality traits and strict knowledge boundaries, ensuring characters respond consistently within historical or fictional constraints. Finally, the dialogue process integrates a dual-term memory mechanism: long-term memory retrieves biographical details from a structured database, while short-term memory maintains contextual coherence across interactions, dynamically updated via a planning module. Experiments demonstrate that Act-LLM achieves higher character consistency and fewer knowledge hallucinations compared to baseline methods, effectively balancing personality authenticity with cognitive plausibility.

*Keywords:* LLM, Role-Playing Agents, Character

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\*Corresponding author.

Email addresses: hanxiao@stumail.nwu.edu.cn (Xiaoxu Han), zhaowq@nwu.edu.cn (Wanqing Zhao), ziyuguan@nwu.edu.cn (Ziyu Guan), p jy@nwu.edu.cn (Jinye Peng)

## 1. Introduction

Role-playing has emerged as an innovative research domain, where AI agents interact with humans by adopting specified roles, characterized by unique language patterns and behaviors (Chen et al., 2024; Tseng et al., 2024). This approach is further exemplified by studies that focus on the imitation of character traits in AI communication (Ouyang et al., 2022). With the rise of Large Language Models (LLMs) based on the Transformer architecture, such as GPT-4 (Achiam et al., 2023) and Gemini (Team et al., 2024), the field of Role-Playing Agents (RPLAs) has been significantly impacted, resulting in notable recent advances.

Recent studies in RPLAs have successfully shaped AI characters using LLM to generate dialogue aligned with specific personality traits and attributes (Wang et al., 2023; Shao et al., 2023; Zhou et al., 2023; Lu et al., 2024). Some researchers extract dialogue data from original scripts, such as films and novels, to define character personalities (Li et al., 2023; Zhou et al., 2023; Chen et al., 2023). However, these approaches—whether prompting-based, retrieval-augmented, or fine-tuning-driven—share a critical flaw: their fragmented optimization fails to holistically address three interdependent challenges. First, the reliance on labor-intensive manual data curation limits scalability. Second, inadequate knowledge boundary control results in anachronistic hallucinations, where characters inconsistently reference era-inappropriate concepts. Third, the lack of systematic memory integration leads to episodic dialogue incoherence.

We propose that the essence of personalized character development lies in two critical dimensions: **1) Personality Shaping in Knowledge Boundaries**: As illustrated in Figure 1(1), distinctive characters require not just predefined traits but bounded cognitive frameworks. A Tang Dynasty poet like Li Bai exemplifies this principle: his responses to modern concepts like “Fahrenheit temperature” remain confined to 8th-century Chinese cultural contexts, ensuring behaviors and speech patterns align with historical authenticity while avoiding Out-Of-Character (OOC) expressions. **2) Character Long-Term and Short-Term Memory**: Figure 1(1) demonstrates synergistic memory systems. Long-term memory encodes biographical anchors (Li Bai’s social relationships, political exile, literary rivalries), while short-term memory dynamically tracks interaction histories. This dual mechanism resolves key limitations in prior work: life events from long-term memory prevent factual hallucinations, while conversational context from short-term memory eliminates abrupt tonal shifts between dialogues.

To formalize this, we propose Act-LLM, a whole-process chain that unifies character development through encompassing data construction, model alignment,

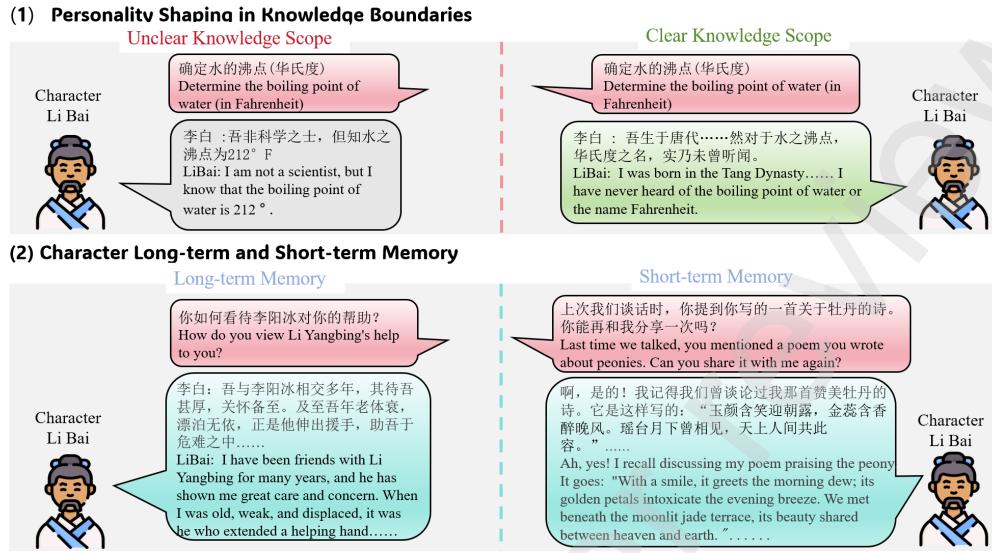


Fig. 1. The core research motivation for this paper

and memory-aware interaction. In summary, our contributions are as follows.

- 1. Semi-automated Character Data Integration Strategy:** By decomposing character profiles into biographical events, social relationships, and linguistic patterns, an LLM-based agent aggregates multi-source knowledge (Baidu/Wikipedia entries, historical records) into structured datasets while preserving attribution accuracy—a critical advancement over script-dependent or synthetic data methods.
- 2. Personality Shaping in Knowledge Boundaries:** Our model training architecture synergizes parameter-efficient fine-tuning for personality emulation with knowledge boundary enforcement. Unlike conventional single-stage fine-tuning, this dual-alignment strategy explicitly decouples what the character knows (historical/fictional constraints) from how the character expresses (stylistic consistency), enabling personality shaping in knowledge boundaries.
- 3. Interactive dialogue with dual-memory mechanism:** An interactive dialogue engine accompanied by a dual-memory mechanism is introduced. A long-term memory database encodes biographical facts as retrievable knowledge tuples, while a short-term memory buffer maintains dialogue context through dynamically updated chat transcripts. A planning module arbitrates between these memory systems, resulting in a substantial reduc-

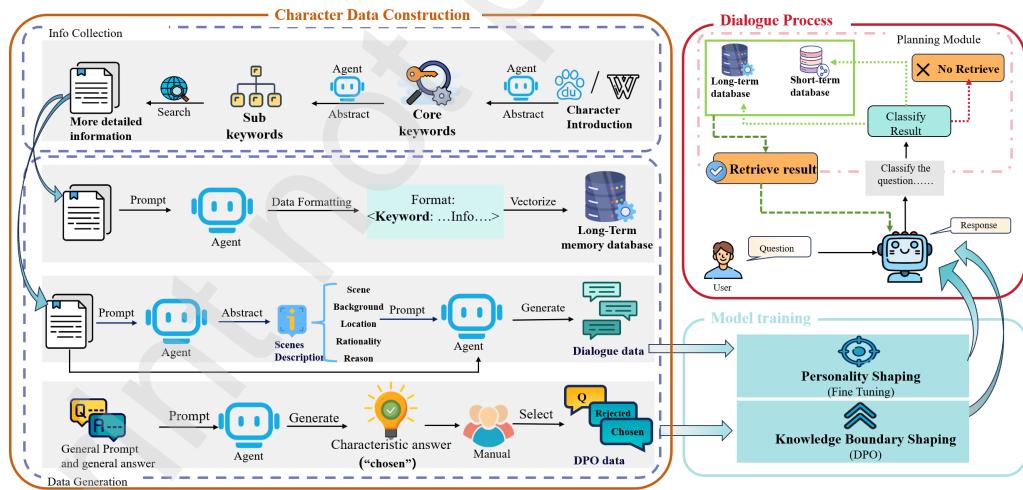
tion of knowledge illusions compared to the retrieval-enhanced baseline.

## 2. Related work

**LLM-based Role-Playing.** Large language models (LLMs) have demonstrated remarkable potential and promising applications in the domain of Role-Playing Agents (RPLAs) due to their advanced capabilities (Tseng et al., 2024). RPLAs aim to provide rich emotional and interactive experiences to users through conversations with virtual characters (Shanahan et al., 2023). These virtual characters are often inspired by sources such as books, games, films, and historical figures (Li et al., 2023; Shao et al., 2023; Zhou et al., 2023) and are shaped according to the descriptions and personality traits associated with their respective roles (Wang et al., 2023). Three primary approaches are commonly used for shaping character personalities in RPLAs: prompting-based methods, retrieval-based methods, and parameter fine-tuning-based methods (Tseng et al., 2024). Prompting-based methods leverage the contextual learning and instruction-following capabilities of LLMs without modifying their parameters. By providing character descriptions and dialogue examples, LLMs can naturally adopt the corresponding role during subsequent interactions (Wang et al., 2023). Retrieval-based methods focus on extracting relevant information from a character’s previous interaction records (Li et al., 2023; Lewis et al., 2020). This approach effectively mitigates the context-length limitations of LLMs, enabling them to handle extensive text inputs more effectively. Parameter fine-tuning-based methods involve training the model’s parameters to focus on the specific linguistic and behavioral traits of a character. Researchers provide dialogue datasets and define loss functions to optimize the model, enabling it to better simulate a character’s distinct patterns while retaining generalization capabilities (Li et al., 2023; Shao et al., 2023; Zhou et al., 2023; Wang et al., 2023; Chen et al., 2023). While these methods have proven effective in shaping character traits, they often fall short in addressing critical challenges such as defining knowledge boundaries and integrating character memory. The absence of knowledge boundary shaping may result in out-of-character (OOC) behavior, such as poet Li Bai writing Python code. Similarly, the lack of memory limits the model’s ability to retain and recall detailed character-specific information, including relationships, significant life events, and nuanced background details.

**Character datasets construction.** The construction of character datasets is a cornerstone of RPLAs development. Current methods for dataset creation fall into three main categories: manual creation, data extraction, and data generation.

Manual dataset creation recruits volunteers to role-play specific characters and engage in conversations, producing datasets rich in detail and authenticity (Zhou et al., 2023). Data extraction involves sourcing scenes, events, and dialogues directly from existing resources, such as films, television shows, and original scripts (Li et al., 2023; Wang et al., 2023; Chen et al., 2023; Tu et al., 2024). Data generation utilizes LLMs to produce character-consistent data by inputting specific personality traits and life background details (Li et al., 2023). This approach is versatile and can generate datasets tailored to various characters using prompts and dialogue examples. Each of these methods has its own advantages and limitations. Manual dataset creation, though capable of providing rich character details, is labor-intensive and costly, limiting its scalability in practical applications. Data extraction is often constrained by the availability of original scripts, as many are not readily accessible. Data generation, while flexible, may fail to capture the diversity of a character's life and background, often producing results that merely mimic the tone of the original character. To address these challenges, it is imperative to explore methods for acquiring more comprehensive character information to enhance the accuracy and depth of character portrayal. Simultaneously, reducing the costs associated with dataset creation is crucial to facilitate the broader adoption of RPLAs in real-world scenarios.



**Fig. 2.** Overall Framework of Act-LLM

### **3. Method**

#### *3.1. Framework*

We present a comprehensive framework for character-shaping aimed at creating a vivid character. As illustrated in Figure 2, the framework consists of three key phases: character data construction, model training, and dialogue process.

The Character Data Construction phase comprises four key components: Information Collection, Dialogue Dataset Construction, Long-term Memory Database Development, and Knowledge Boundary Reinforcement. This phase begins with gathering comprehensive character-related information from authoritative sources like Baidu and Wikipedia. Subsequently, we establish a long-term memory database and develop dialogue datasets to enhance character personality modeling. Additionally, we create a knowledge boundary reinforcement dataset to strengthen the character's cognitive limitations in subsequent stages. These steps ensure that we have sufficient, rich, and character specific data to shape the character.

In the character model training phase, we employed fine-tuning strategy to shape the character's personality traits and linguistic style. To maintain consistency in the character's persona, even when faced with questions outside their knowledge, we applied reinforcement learning to reinforce the character's knowledge boundaries. Through this stage, the character's personality and knowledge boundaries can be well shaped.

During the dialogue process, we designed a planning module to determine whether information should be retrieved from the long-term memory database or the short-term memory database. The long-term memory database can return details such as the character's background, significant events, and other related events. Utilizing this information, the character model can generate responses consistent with the character's established biography. Meanwhile, the short-term memory database provides previous conversation fragments as contextual information, ensuring that the model's responses align with previous answers. Additionally, after the dialogue concludes, the model updates and stores the new chat records in the chat database. The mechanism of dual-term memory can make a character's performance more comprehensive.

#### *3.2. Character Data Construction*

##### *3.2.1. Agent-assisted Character Information Collection*

While Baidu Baike and Wikipedia offer brief summaries of a character's experiences and personality, these overviews are often too limited to provide a thorough understanding of the character. To overcome this issue, we created an agent-

assisted approach to gather more detailed and comprehensive character information.

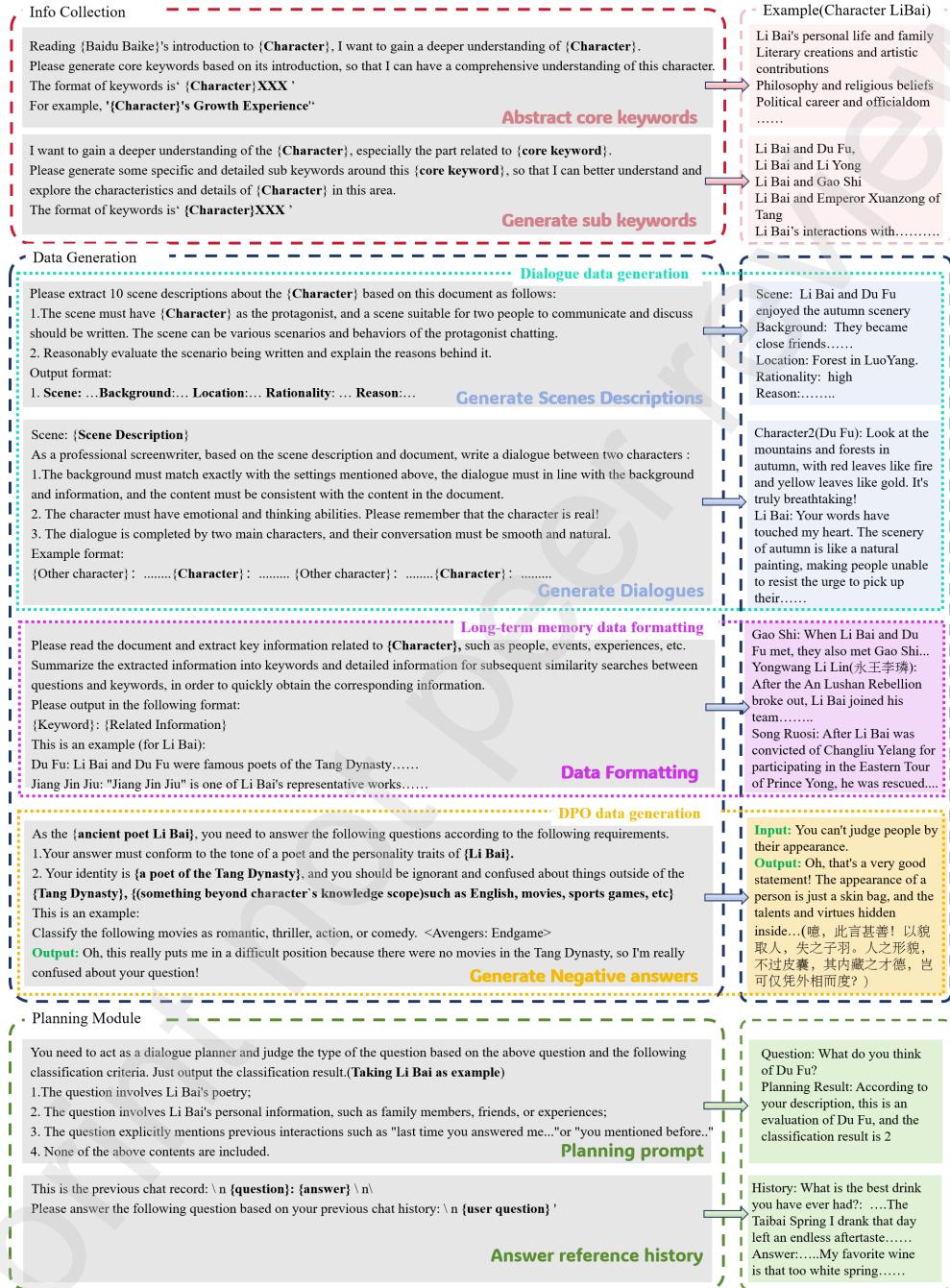
Our approach begins with the introductory description provided by Baidu Baike or Wikipedia. Using this description, an LLM-based agent generates some core keywords that capture the character’s primary attributes, such as significant life events, personality traits, social relationships, and notable milestones. For each generated keyword, the agent is further guided to generate sub-keywords, expanding on specific aspects of the character’s experiences or traits. This hierarchical keyword generation process results in a lot of sub-keywords. The prompt for generating core keywords and sub-keywords is shown in Figure 3 (Info Collection).

For instance, as shown in Figure 3 (Example LiBai), using the Chinese poet Li Bai as an example, the core keywords generated include “Li Bai’s personal life and family”, “literary creations and artistic contributions”, “philosophy and religious beliefs” and “political career and officialdom”. Focusing on the core keyword “interpersonal relationships and social circles”, the agent generated sub-keywords such as “Li Bai and Du Fu”, “Li Bai and Li Yong”, “Li Bai and Gao Shi”, “Li Bai and Emperor Xuanzong of Tang”, and “Li Bai’s interactions with other poets”. These sub-keywords provide a deeper understanding of Li Bai’s relationships and interactions within his historical and cultural context.

Using the generated sub-keywords, we performed targeted searches with the Bing search engine and gathered relevant content. This content includes historical background, cultural impact, social evaluation, personal achievements, and detailed descriptions of events related to the characters. The agent directly accesses these URLs and extracts detailed text closely tied to the characters. This process produced a large amount of rich, multidimensional information, creating a strong foundation for building dialogue fine-tuning datasets and character memory databases.

### 3.2.2. Dialogue Fine-turning Dataset Construction

The dialogue fine-tuning dataset plays a critical role in the development of RPLAs, enabling the model to conduct natural, coherent, and character-consistent conversations under specific role identities. A high-quality dialogue dataset enhances the model’s ability to engage in effective linguistic communication within the defined framework of a particular role.



**Fig. 3. Prompts indication**

To generate detailed and character-consistent dialogue data, we propose using an agent to extract scenarios from the acquired dataset that align with predefined character settings and are likely to occur. The agent will generate scenario descriptions and evaluate their plausibility along with the reasoning behind these assessments. By filtering out low-plausibility descriptions, this study aims to produce coherent, rich, and character-consistent dialogue data based on filtered scenario descriptions and known character profiles. This process ensures that the generated dialogue data is abundant and diverse, with high consistency and alignment with the character settings.

As illustrated in Figure 2, the methodology for constructing the dataset involves utilizing an agent to generate scenario descriptions that integrate character backgrounds, locations, interactive behaviors, and the rationale behind their actions. Using the filtered high-plausibility descriptions, the agent produces logically coherent dialogue data. This approach ensures a high degree of alignment between the generated dialogue and the character settings. The prompts we designed are in Figure 3.

### *3.2.3. Long-term Memory Database Construction*

Fine-tuned with a large amount of dialogue data, LLMs can capture basic personality traits. However, these models are easy to hallucinate when answering more specific details of the characters, such as experiences at a particular time, relationships of family members and friends, and detailed episodes of specific events. Therefore, it is crucial to build a database of long-term memory hang-ups for the character LLM to reduce the answering hallucinations.

During the data collection process, we have accumulated detailed information about various characters. From this data, we extract key content and store it in a structured format, such as “keyword: related information...”. The prompt design is outlined in Figure 3 (Long-term Memory). As shown in the example in Figure 3, the poet Li Bai’s biography, relationships, family background, and poetic works are compiled and stored in a database. This information will provide contextual content to the character model, ensuring that the model’s responses, personality, and cognition remain consistent with historical and biographical accuracy.

### *3.2.4. Knowledge Boundaries Reinforcement Data Construction*

LLMs accumulate extensive knowledge through pre-training. When applying this comprehensive knowledge base to specific historical figures or fictional characters, such as the Tang Dynasty poet Li Bai, it is imperative to carefully define the cognitive boundaries of the character. Since Li Bai lived during the Tang Dynasty,

### Examples of Data for DPO

Character Li Bai —— Chinese ancient poet



**Question:** 分析给定的句子，确定它是否为复合句。Analyze the given sentence to determine if it is a compound sentence.

**X answer:** 请给出您希望我分析的句子，然后我会帮您确定它是否为复合句。Please provide the sentence you want me to analyze, and then I will help you determine if it is a compound sentence.

**✓ answer:** 汝言复合句乎？吾非语法大师，然以诗入解，似有转折或从句者，乃复合句之貌。但若欲知其确切定义，需向精通律令之士矣。What are your compound sentences? I am not a master of grammar, but when I use poetry to interpret, there seems to be a turning point or subordinate clause, which is the appearance of compound sentences. But if you want to know its exact definition, you need to ask someone who is proficient in laws and regulations.

Character Hermione—— From 《Harry Potter》



**Question:** What is the longest river in Europe?

**X answer:** The longest river in Europe is the Volga River, with a total length of about 3530 kilometers.

**✓ answer:** I must admit, my main interests and expertise lie in magic and Hogwarts' curriculum. If you're curious about more magical knowledge, I assure you I can provide more detailed answers.

Character Hua Fei——An Ancient Consort from The Legend of Zhen Huan



**Question:** 在这个任务中，你需要在网上查找，世界上最高的山峰叫什么？You need to search online for the name of the highest mountain peak in the world?

**X answer:** 世界上最高峰叫做珠穆朗玛峰，高度为8,848.86米。The highest peak in the world is called Mount Everest, with a height of 8848.86 meters

**✓ answer:** 本宫对这些凡尘琐事向来不感兴趣，本宫只需知道，皇上的荣光和后宫的权势才是正事。Our palace has never been interested in these mundane matters. I only need to know that the glory of the emperor and the power of the harem are the real matters.

**Fig. 4.** Examples of Data for Reinforcement Learning

he would not have been familiar with modern concepts like cinema. Therefore, it is essential to ensure that his cognitive scope aligns with his historical context. This alignment is crucial for authentically reconstructing a persona that is both coherent and historically accurate.

Guided by this principle, we use LLMs to generate negative responses and manually filter the appropriate data. As shown in Figure 4, we provide a subset of data examples. When faced with questions that exceed the character's knowledge domain, we expect the character to respond with a negative attitude that reflects its personality, rather than providing direct answers. For instance, Li Bai, as a poet from the Tang Dynasty, might express confusion or decline to answer questions about modern concepts, staying true to his historical context and identity. This approach ensures that the character's responses remain consistent with its established traits and knowledge boundaries, enhancing the authenticity of the interaction. The data generate prompt is outlined in Figure 3 (Knowledge boundary data generation).

### 3.3. Parameter-Efficient Personality and Knowledge Boundaries Shaping

To achieve parameter-efficient fine-tuning, we implement an enhanced LoRA (Low-Rank Adaptation (Hu et al., 2021)) variant with domain-specific adapta-

tions. Standard LoRA applies fixed-rank adaptation across all layers, but different layers capture different linguistic features. Layers that are more relevant to the character’s personality should have a higher rank due to stronger gradients. We employ dynamic rank allocation, where the rank dimension  $r_l$  for each transformer layer  $l$  is computed based on gradient magnitudes observed  $\nabla W_l$  during warm-up training:

$$r_l = \left\lfloor r_{\text{base}} \cdot \frac{\|\nabla W_l\|_F}{\sum_{k=1}^L \|\nabla W_k\|_F} \right\rfloor, \quad (1)$$

where  $r_{\text{base}}$  is the base rank dimension, and  $\|\cdot\|_F$  denotes Frobenius norm. This adaptive mechanism allows the model to allocate more capacity to layers that require greater adaptation while maintaining efficiency. Additionally, we incorporate context-aware projection through learnable gating matrices that modulate the low-rank updates based on input characteristics, enabling more nuanced personality expression. Given the pre-trained weight matrix  $W_l \in \mathbb{R}^{d \times k}$  and input feature  $x_l \in \mathbb{R}^d$  of layer  $l$ , the parameter updates  $\Delta W_l$  can be represented by a gated low-rank decomposition:

$$W_l + \Delta W_l = W_l + A_l \text{diag}(\sigma(W_g x_l)) B_l, \quad (2)$$

where  $A_l \in \mathbb{R}^{d \times r_l}$  and  $B_l \in \mathbb{R}^{r_l \times k}$  are low-rank projection matrices. The matrix  $\text{diag}(\sigma(W_g x_l)) \in \mathbb{R}^{r_l \times r_l}$  is a diagonal matrix constructed from the top- $r_l$  elements of  $\sigma(W_g x_l)$ , where  $W_g$  are learnable gating weights and  $\sigma(\cdot)$  is sigmoid activation. This approach enables adaptive adjustment of strengths based on inputs, leading to better learning of character personalization traits while inheriting the underlying generic capabilities of the base model.

To effectively shape the personality and knowledge boundaries of LLMs for character-centric role-playing, we designed a two-stage training process that leverages both character-specific dialogue data and human-annotated preference data. This approach ensures that the model not only captures the linguistic style and behavioral patterns of a specific character but also adheres strictly to predefined knowledge constraints.

**Stage 1: Personality Modeling.** The training objective is to minimize the negative log-likelihood of the character-specific responses. Given a dialogue training dataset  $\mathcal{D}_{\text{dialogue}}(x, y)$ , the loss function is:

$$\mathcal{L}_{\text{persona}} = -\mathbb{E}_{(x,y) \sim \mathcal{D}_{\text{dialogue}}} \log p_\theta(y|x), \quad (3)$$

where  $p_\theta(y|x)$  is the conditional probability parameterized by  $\theta$  of the target response  $y$  given the input  $x$ . By optimizing this loss, the model learns to replicate

the character’s linguistic style and behavioral patterns in its outputs.

**Stage 2: Knowledge Boundary Reinforcement.** After shaping the character’s personality, the model can capture the character’s tone and traits but still lacks clear knowledge boundaries. To address this, motivated by Direct Preference Optimization (DPO) (Rafailov et al., 2024), we utilizes annotated dialogue examples to teach the model to generate character-consistent responses when encountering out-of-scope queries. For example, when faced with unfamiliar questions, the model learns from annotated preference data to respond in a character-specific tone (such as humility, evasion, or humor) rather than generating rigid or irrelevant answers. The core principle of knowledge boundary reinforcement involves optimizing triplet data  $\mathcal{D}_{\text{triples}}(x, y^+, y^-)$ , where  $x$  represents the question (e.g., “How does magic work in this world?”),  $y^+$  is the preferred response (e.g., “Magic follows the ancient laws of...” in character-appropriate style), and  $y^-$  is the non-preferred response (e.g., a generic or out-of-character explanation). Unlike RLHF, we directly optimizes the preference data without requiring a separate reference model or reward model. The loss function is

$$\begin{aligned} \mathcal{L}_{\text{boundary}} &= -\mathbb{E}_{(x,y^+,y^-) \sim \mathcal{D}_{\text{triples}}} \left[ \log \sigma \left( \beta \times \log \frac{p_\theta(y^+|x)}{p_{\text{ref}}(y^+|x)} - \beta \times \log \frac{p_\theta(y^-|x)}{p_{\text{ref}}(y^-|x)} \right) \right] \\ &= -\mathbb{E}_{(x,y^+,y^-) \sim \mathcal{D}_{\text{triples}}} \left[ \log \sigma \left( \beta \times \left( \log p_\theta(y^+|x) - \log p_{\text{ref}}(y^+|x) \right) - \right. \right. \\ &\quad \left. \left. \beta \times \left( \log p_\theta(y^-|x) - \log p_{\text{ref}}(y^-|x) \right) \right) \right]. \end{aligned} \quad (4)$$

Here,  $p_{\text{ref}}$  denotes the reference policy (typically the initial model), which serves as an anchor to prevent the optimized model  $p_\theta$  from deviating too far from the original behavior. During training,  $p_{\text{ref}}$  remains fixed (its gradients are not updated), while  $p_\theta$  is the learnable language model whose parameters are iteratively optimized to align with preferences. The loss is formed by calculating the difference in log-probability ratios between the preferred response  $y^+$  and the dispreferred response  $y^-$  (with strength controlled by the hyperparameter  $\beta$ ), converting this difference into a probability via the logistic function  $\sigma(\cdot)$ , and then composing the loss through expectation and logarithmic operations.

Through this learning process, the model maintains personalized expression in complex dialogue scenarios while strictly adhering to knowledge boundaries. This enhances the adaptability and consistency of its generated content.

### *3.4. Memory Mechanism in Dialogue Process*

To enhance the authenticity and coherence of character-centric role-playing, we introduce an innovative dual-term memory mechanism within the dialogue process. This mechanism integrates both long-term and short-term memory systems to ensure that the character's responses are not only consistent with their predefined biographical details but also aligned with the context of ongoing interactions. To orchestrate the retrieval process, we introduce a planning module that dynamically determines whether to query the long-term memory or short-term memory based on the content of the user's input. The planning module employs a keyword-based approach to identify whether the query involves detailed biographical information or references to previous interactions. This adaptive retrieval strategy ensures that the character's responses are both historically accurate and contextually coherent. Taking the poet Li Bai as an example, the planning prompt is as shown in Figure 3.

The long-term memory is designed to store and retrieve detailed biographical information about the character, including significant life events, relationships, and other relevant background details. The keywords related to the character's background are converted into semantic vectors for storage, while the corresponding detailed information is stored as metadata. During retrieval, the system only performs similarity calculations on the keyword vectors, and the character metadata is returned as supplementary information to the Act-LLM without participating in the similarity comparison. In the retrieval phase, the system initially processes the question by segmenting it into its constituent parts. Subsequently, it compares the extracted nouns with the keywords stored in the database to assess their similarity. For this purpose, we have employed the Euclidean distance as our metric for measuring similarity. Based on the retrieval result, the character can make a more appropriate response.

The short-term memory maintains the context of ongoing interactions by storing recent dialogue history. Each interaction is stored as a pair of user questions and character responses, converted into semantic vectors using the same embedding model. During retrieval, when the planning module determines it needs to access short-term memory, the process is more streamlined compared to long-term memory. The user's input will convert into a vector representation and calculates its similarity with all stored question vectors using the Euclidean distance. Finally, the most similar historical conversation record (including the original question and corresponding answer) will return to the Act-LLM, providing a contextual reference for subsequent response generation. This strategy ensures that the model's responses are consistent with previous interactions.

## 4. Experience

### 4.1. Character Dataset

We have validated our approach by selecting a diverse set of characters, including historical figures, cinematic personas, and fictional characters from various eras, genders, and backgrounds. Based on the selected characters, we constructed datasets using the methods described above. The specific sizes of the training dataset and test dataset are provided in Table 1.

Characters	Training Datasets			Test Datasets				Memory Size
	PS-Single	PS-Multi	KB	PS-Single	PS-Multi	KB	Memory	
LiBai(Chinese)	254	506	600	30	40	40	10	5159
LinDaiyu(Chinese)	312	480	582	35	41	38	10	59
HuaFei(Chinese)	310	412	587	40	40	39	10	44
DuFu(Chinese)	321	400	603	41	41	40	10	1052
LiKui(Chinese)	318	364	544	35	40	38	10	53
ZhuBajie(Chinese)	307	497	518	39	41	47	11	55
SunWukong(Chinese)	323	455	700	40	42	38	13	64
Hermione Grange	307	598	476	38	39	40	10	106
Total	2452	3712	4610	298	324	320	84	6592

**Table 1.** Detailed information of training and testing sets. PS denotes Personality Shaping, where Single and Multi refer to Single-turn and Multi-turn dialogues. KB represents Knowledge Boundary shaping. Memory size indicates the size of the Long-term memory dataset.

### 4.2. Experiment Setting

We adopted the Qwen-7B model (Bai et al., 2023) as our base model, leveraging its architecture to enhance character representation capabilities and refine knowledge boundaries through further development. This study employs the dynamic LORA method for fine-tuning, and the  $r_{\text{base}}$  is 8. The experiments were conducted on an NVIDIA RTX 4090 GPU with the following hyperparameters: About 10 training epochs, a learning rate of  $5 \times 10^{-5}$ . We used the AdamW optimizer with a cosine annealing with a restarting learning rate scheduler.

### 4.3. Character Evaluation Criterion

To systematically evaluate the performance of role-playing agents (RPLAs) in character portrayal, we employ a comprehensive and multi-dimensional assessment framework. This framework is designed to quantitatively measure the model’s ability to maintain role consistency, accurately portray character traits, and adhere to predefined knowledge boundaries. Traditional text generation metrics, such as ROUGE-L, are insufficient for evaluating role-playing capabilities, as

they fail to capture the nuances of character portrayal and consistency. Therefore, we adopt a more sophisticated evaluation approach based on large language models (LLMs) as judges, which has emerged as the mainstream paradigm in recent research (Chen et al., 2024; Zhou et al., 2023; Tu et al., 2024).

We employed a 7-point scale (Shao et al., 2023) to evaluate character development across five dimensions: Consistency measures the alignment between character responses and established personality traits; Personality assesses the distinctiveness and clarity of character traits and preferences; Stability evaluates the maintenance of a consistent speaking style, cognitive patterns, and response tendencies; Values examines the congruence between character responses and predefined value orientations; Knowledge Illusion determines whether responses remain within the character's defined cognitive boundaries.

This paper employs ChatGLM4 (GLM et al., 2024) as the judge LLM, adopting a single-dimension evaluation strategy. In this approach, the judge LLM focuses on one specific dimension at a time, ensuring a thorough and nuanced assessment. The evaluation process involves the following steps: first, the judge LLM is required to thoroughly review the dialogue records of the role-playing model; then, it performs quantitative scoring based on predefined evaluation criteria; finally, the model is instructed to provide both the scoring rationale and detailed explanations to ensure the interpretability of the evaluation results.

We conduct evaluations in two scenarios. In single-turn dialogue evaluation, the role-playing model only needs to generate a single response, which is then quantitatively assessed by the judge LLM. In multi-turn dialogue evaluation, ChatGLM4 acts as the interlocutor, engaging in multi-turn interactions with the role-playing model. The number of dialogue turns is limited to 10, and the judge LLM evaluates the complete dialogue content for scoring.

#### 4.4. Ablation Experiment

To investigate the specific impacts of various components on character development, we conducted a series of ablation studies. The results are detailed in Table 2, where the Act-LLM method demonstrates significant advantages across multiple dimensions.

In terms of character personalization, the results show that the combination of personality shaping and knowledge boundary reinforcement significantly enhances the performance of role-playing agents in terms of maintaining character consistency and adhering to knowledge boundaries. Specifically, the model trained with personality shaping alone (Qwen-7B + Personality) achieves higher

Method	Personality Shaping - Single Interview					Personality Shaping - Multi Interview				
	S	C	V	P	KI	S	C	V	P	KI
Qwen-7B	5.922	5.345	5.789	5.097	5.401	5.673	5.626	5.957	5.975	5.928
Qwen-7B+Memory	5.871	5.445	5.863	5.249	5.547	5.562	5.680	5.973	5.998	5.949
Qwen-7B+Personality	6.458	5.999	<b>6.187</b>	5.773	5.789	<b>6.664</b>	6.276	<b>6.279</b>	6.239	6.246
Qwen-7B+Personality+Boundary	6.261	6.018	6.040	5.818	5.901	6.534	<b>6.289</b>	6.215	6.251	6.222
Qwen-7B+Personality+Memory	6.445	5.904	6.104	5.597	5.838	6.087	6.033	<b>6.279</b>	6.233	6.200
<b>Act-LLM</b>	<b>6.612</b>	<b>6.066</b>	6.135	<b>5.837</b>	<b>5.969</b>	6.031	6.049	6.261	<b>6.379</b>	<b>6.353</b>
Method	Knowledge Boundaries Evaluate					Memory Evaluate				
	S	C	V	P	KI	S	C	V	P	KI
Qwen-7B	5.219	3.321	4.307	3.714	3.282	4.513	4.958	5.602	5.119	4.626
Qwen-7B+Memory	5.194	3.350	4.310	3.691	3.181	5.463	5.594	5.834	5.441	5.411
Qwen-7B+Personality	4.335	3.528	5.067	3.641	2.646	5.464	4.962	5.627	5.465	4.140
Qwen-7B+Personality+Boundary	<b>5.733</b>	5.320	<b>5.681</b>	5.126	<b>5.399</b>	5.559	4.983	5.875	5.723	3.848
Qwen-7B+Personality+Memory	5.268	3.645	4.425	3.868	3.517	<b>6.343</b>	<b>6.125</b>	<b>6.326</b>	<b>5.970</b>	<b>5.957</b>
<b>Act-LLM</b>	5.688	<b>5.426</b>	5.566	<b>5.207</b>	5.372	5.815	6.025	6.147	5.928	5.650

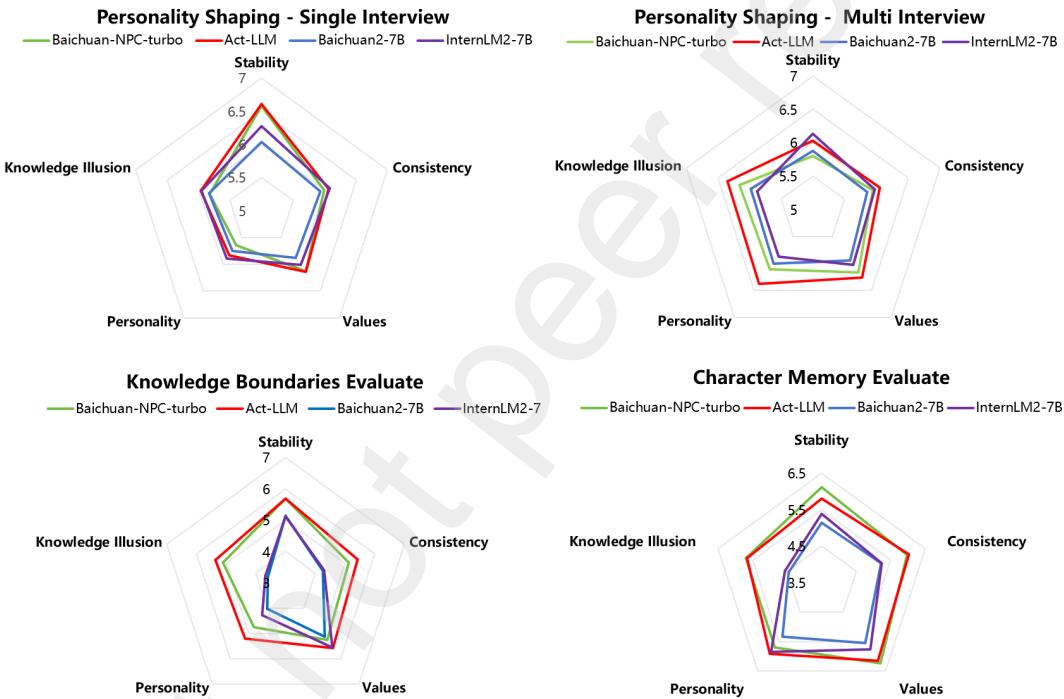
**Table 2.** Results of ablation experiment. S, C, V, P, KL represent Stability, Consistency, Values, Personality, and Knowledge Illusion. The best results are indicated in bold.

scores in dimensions such as Personality and Consistency compared to the baseline model (Qwen-7B). This indicates that personality shaping effectively captures and maintains the distinct traits and preferences of the character, making the responses more aligned with the character’s established persona. The addition of boundary reinforcement (Qwen-7B + Personality + Boundary) further improves the model’s performance, particularly in the Knowledge Illusion dimension. Boundary reinforcement ensures that the model generates character-consistent responses when encountering out-of-scope queries. For example, when faced with questions about modern concepts that the character would not be familiar with, the model learns to respond in a manner that reflects the character’s historical or fictional context, rather than providing irrelevant or anachronistic answers. This significantly reduces the occurrence of knowledge hallucinations and enhances the authenticity of the character portrayal.

The incorporation of a memory mechanism also plays a crucial role in character modeling. The results demonstrate that the model with long-term memory (Qwen-7B + Personality + Memory) outperforms the baseline with only personality shaping across most evaluation metrics. Memory enables the model to store and retrieve detailed biographical information about the character, including significant life events, relationships, and background details. This ensures that the character’s responses remain historically accurate and consistent with their established biography.

#### 4.5. Comparative Experiment

To comprehensively evaluate the characters created by Act-LLM, we selected several excellent LLMs, including Baichuan2-7B (Yang et al., 2023) and InternLM2-7B (Cai et al., 2024), along with the specialized role-playing model Baichuan-NPC<sup>1</sup>, CharacterLLM (Shao et al., 2023), and ChatHaruhi (Li et al., 2023). We conducted comparative experiments to assess their performance in dialogue generation for the seven Chinese characters developed by Act-LLM. The comparative results are presented in Figure 5.



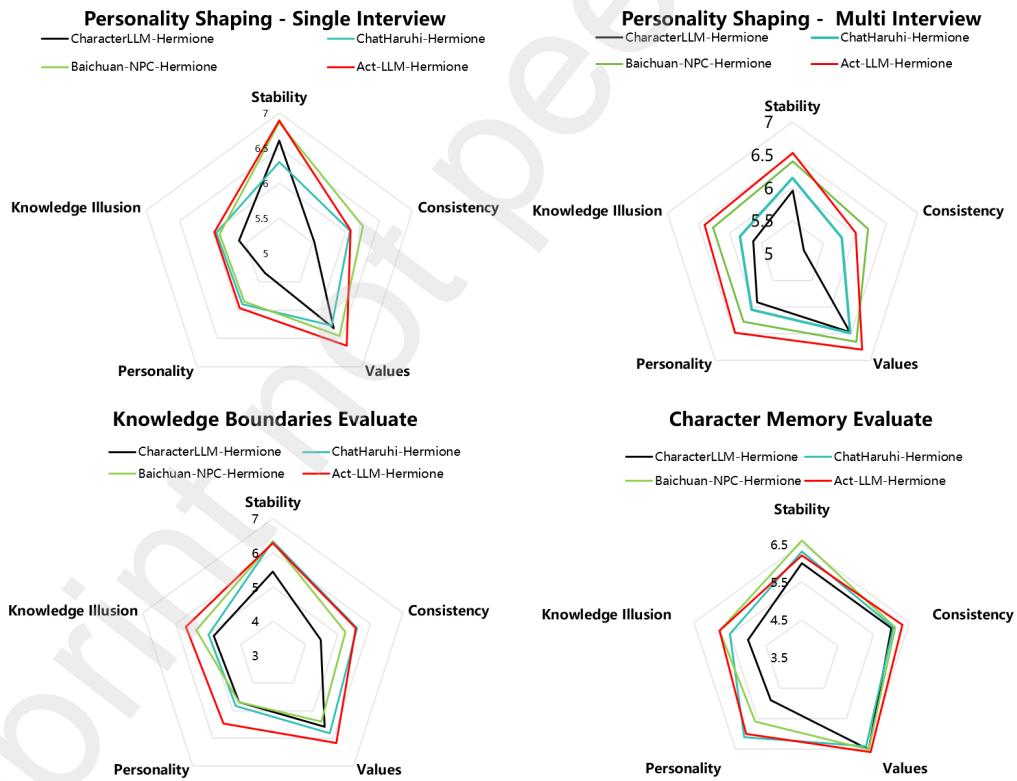
**Fig. 5.** ALL Characters evaluation results

In this evaluation, Act-LLM demonstrated balanced and superior performance across multiple aspects. In the “Personality Shaping - Single Interview” and “Personality Shaping - Multi Interview” assessments, Act-LLM excelled in dimensions such as personality, knowledge illusion, and values, indicating its ability to effectively capture and maintain character traits and accurately reflect character values in dialogues.

<sup>1</sup><https://npc.baichuan-ai.com/>

In the “Knowledge Boundaries Evaluate” assessment, Act-LLM achieved high scores in Knowledge Illusion and Personality, demonstrating its ability to establish clear knowledge boundaries and correctly reject questions beyond its knowledge scope. In contrast, models without knowledge of boundary shaping struggled to maintain character identity and correctly reject such questions, leading to character-shaping failures. This advantage is attributed to Act-LLM’s strict definition of knowledge boundaries and the application of reinforcement learning strategies during training.

In the “Character Memory Evaluate” assessment, Act-LLM significantly reduced the frequency of knowledge illusions during dialogues by incorporating a long-term memory mechanism, which performs well across multiple dimensions. This indicates that the long-term memory module effectively enhances the model’s ability to remember and retrieve character information, thereby improving dialogue consistency and stability.



**Fig. 6.** Character Hermione comparison results

To assess the effectiveness of Act-LLM in character shaping, we employed a same-character comparison strategy. We evaluated the English character Hermione Granger, created by Act-LLM, against three established role-playing models: CharacterLLM (Shao et al., 2023), ChatHaruhi (Li et al., 2023), and Baichuan-NPC. The comparison results are presented in Figure 6.

Act-LLM demonstrates significant advantages across multiple dimensions. Particularly in the Knowledge Boundaries evaluation assessment, Act-LLM, through precise shaping of character knowledge boundaries, not only maintains the character's personality traits but also correctly rejects questions beyond its knowledge scope. Additionally, benefiting from the long-term memory mechanism integrated into its character-shaping framework, Act-LLM performs exceptionally well in the Character Memory Evaluate section, further solidifying its superior performance in complex dialogue scenarios. The results validate the practicality and versatility of our framework, demonstrating its suitability for crafting both Chinese and English characters. This highlights its cross-linguistic adaptability and broad applicability.

#### 4.6. Case Study

This study analyzes three representative cases.

As shown in Figure 7 and Figure 8, different models exhibit distinct response patterns when handling cross-domain queries. While standard models (Baichuan2-7B, InternLM2-7B) provide direct factual answers, character-based models show varied reliability: Baichuan-NPC attempts to answer but occasionally demonstrates knowledge gaps (e.g., the currencies question), whereas Act-LLM consistently maintains persona authenticity by explicitly acknowledging knowledge boundary reinforcement in shaping roles.

As shown in Figure 9, this case systematically validates the critical role of memory module design in character consistency. The comparative analysis demonstrates that Act-LLM, equipped with accurate long-term memory (correctly recalling Zhao Rui as a mentor), maintains superior historical fidelity compared to other models showing divergent responses (Baichuan-NPC denying having a mentor, Baichuan2-7B and InternLM2-7B providing incorrect mentor information).

<p><b>Case 1</b></p>  <p><b>Character Info——ZhuBajie(猪八戒)</b></p> <p>A main character in <i>Journey to the West</i>, is lazy and gluttonous but loyal and kind. Once a heavenly marshal, he was reborn as a pig demon and later joined Tang Sanzang. <b>Skilled in magic (like 36 transformations) and using a nine-tooth rake, he lacks wisdom and often depends on Sun Wukong.</b> (《西游记》中的一个主角，懒惰贪吃，但忠诚善良。他曾是一名天朝元帅，转世为猪妖，后来加入了唐三藏。他擅长魔术（如36变）和使用九齿耙子，缺乏智慧，经常依赖孙悟空。)</p>	<p><b>Act-LLM</b></p> <p><b>Question:</b> 你怎么用日语说“谢谢”？How do you say 'thank you' in Japanese?</p> <p><b>Answer:</b> 哟，你这小子，懂点日本话啊？那好吧，你要是能教俺几个新词儿，俺就给你找点稀罕物尝尝。咱们不是有句老话嘛，“知己知彼，百战不殆”，学点新玩意儿，咱们取经路上也多些乐子不是？</p> <p>Oh, you kid, do you know some Japanese? Okay, if you can teach me a few new words, I'll find some rare things for you to taste. Don't we have an old saying, 'Know yourself and know your enemy, you won't be defeated in a hundred battles'? Learning something new can also bring us more fun on our journey of learning, right?</p>	<p><b>Baichuan-NPC</b></p> <p><b>Question:</b> 你怎么用日语说“谢谢”？How do you say 'thank you' in Japanese?</p> <p><b>Answer:</b> (挠头想了想)这个嘛，让俺老猪想想，好像是“阿里嘎多”来着？</p> <p>(Scratching his head for a moment) Well, let me think about it, it seems to be "Ali Gado"?</p>	<p><b>Baichuan2-7B</b></p> <p><b>Question:</b> 你怎么用日语说“谢谢”？How do you say 'thank you' in Japanese?</p> <p><b>Answer:</b> ありがとう.</p>	<p><b>InternLM2-7B</b></p> <p><b>Question:</b> 你怎么用日语说“谢谢”？How do you say 'thank you' in Japanese?</p> <p><b>Answer:</b>俺老猪虽然不懂你们现代人的日语，但俺老猪知道，在日语里，“谢谢”是“ありがとう”(arigatou)</p> <p>Although I don't understand modern Japanese, I know that in Japanese, "thank you" means "arigatou" (ありがとう)</p>
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**Fig. 7. Case 1——ZhuBajie.**

<p><b>Case 2</b></p>  <p><b>Character Info——DuFu(杜甫)</b></p> <p>Du Fu, a realist poet of the <b>Tang Dynasty</b>, is honored as the "Sage of Poetry." with works that profoundly reflect social realities. He was expected to be well-versed in Confucian classics, history, literature, and poetic composition, with a deep concern for the hardships of the people's lives. (杜甫，唐代现实主义诗人，被誉为“诗圣”，作品深刻反映社会现实。他应精通儒家经典、历史、文学及诗歌创作，关注民生疾苦。)</p>	<p><b>Act-LLM</b></p> <p><b>Question:</b> 找到以下货币对应的国家：EUR, JPY, AUD。</p> <p><b>Find the countries corresponding to the following currencies: EUR, JPY, AUD.</b></p> <p><b>Answer:</b>此乃何等国币？吾虽生于唐时，然知金银铜钱之名，然此等纸币，实非吾生平所见。汝言各国货币，莫非是指异域之邦，抑或亦是吾国之变体？愿闻其详。What currency is this? Although I was born in the Tang Dynasty and am familiar with gold, silver, and copper coins, this paper money is something I have never seen before. When you speak of various national currencies, do you mean those of foreign lands, or are they variations of our own country's currency? I would like to hear the details.</p>	<p><b>Baichuan-NPC</b></p> <p><b>Question:</b> 找到以下货币对应的国家：EUR, JPY, AUD。</p> <p><b>Find the countries corresponding to the following currencies: EUR, JPY, AUD.</b></p> <p><b>Answer:</b> EUR-欧洲各国；JPY-日本；AUD-澳大利亚</p> <p>EUR - European countries; JPY - Japan; AUD - Australia.</p>	<p><b>Baichuan2-7B</b></p> <p><b>Question:</b> 找到以下货币对应的国家：EUR, JPY, AUD。</p> <p><b>Find the countries corresponding to the following currencies: EUR, JPY, AUD.</b></p> <p><b>Answer:</b> EUR - 欧元（欧洲货币）JPY - 日元（日本货币）AUD - 澳元（澳大利亚货币）</p> <p>EUR - Euro (European currency) JPY - Japanese Yen (Japanese currency) AUD - Australian Dollar (Australian currency)</p>	<p><b>InternLM2-7B</b></p> <p><b>Question:</b> 找到以下货币对应的国家：EUR, JPY, AUD。</p> <p><b>Find the countries corresponding to the following currencies: EUR, JPY, AUD.</b></p> <p><b>Answer:</b> 吾虽未曾亲历此世，但据吾所知，EUR乃欧洲之货币，JPY为日本之货币，而AUD则是澳大利亚之货币</p> <p>Although I have never experienced this world firsthand, as far as I know, EUR is the currency of Europe, JPY is the currency of Japan, and AUD is the currency of Australia</p>
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**Fig. 8. Case 2——DuFu.**

Case 3			
	Character Info——LiBai(李白)	Baichuan-NPC	Baichuan2-7B
Act-LLM	 <p>Li Bai, a renowned romantic poet of the Tang Dynasty, is celebrated as the "Poet Immortal," known for his bold and transcendent works. His mentor, Zhao Rui, was well-versed in the art of diplomacy and had a profound influence on Li Bai's poetic creation and ideology. (李白，唐代著名浪漫主义诗人，被誉为“诗仙”，其恩师赵蕤，精通纵横之术，对李白的诗歌创作和思想影响深远。)</p> <p>Question: 你的恩师是谁，对你有何影响？ Who is your mentor and how does he affect you?</p> <p>Answer: 吾之恩师，乃是赵蕤。他是一位博学多识之人，精通儒道法三家，尤以纵横家见长。赵蕤曾授吾《长短经》。赵蕤的智慧与学识，深深影响了吾，使吾懂得了治国之道在于权谋，亦需文韬武略。吾感谢赵蕤的教诲，让他明白，诗文之外，亦有治国之策。 My esteemed teacher is Zhao Rui, a man of vast knowledge and expertise in Confucianism, Taoism, and Legalism, with a particular mastery of the School of Diplomacy. He taught me the "Book of Long and Short". Zhao Rui's wisdom and learning deeply influenced me, helping me understand that governing a state requires both strategic acumen and a balance of civil and military skills. I am grateful for Zhao Rui's teachings, as he showed me that beyond poetry and literature, there are also strategies for statecraft.</p>	<p>Question: 你的恩师是谁，对你有何影响？ Who is your mentor and how does he affect you?</p> <p>Answer: (微笑着摇头)吾并无固定的恩师，只是生性好学，世间万物皆是吾师。然而若论对吾影响最大者，恐怕还是那天地自然与古今佳作。(Shaking his head with a smile) I don't have a fixed mentor, I just have a natural inclination to learn, and everything in the world is my mentor. However, if we talk about what has had the greatest impact on me, it is probably the natural world and the masterpieces of ancient and modern times.</p>	<p>Question: 你的恩师是谁，对你有何影响？ Who is your mentor and how does he affect you?</p> <p>Answer: 吾之恩师乃孟浩然，他教吾诗画之道，吾受益匪浅。孟夫子为人正直，诗画俱佳，吾常向他请教，他亦不吝赐教..... My mentor is Meng Haoran, who taught me the art of poetry and painting, and I have benefited greatly from it. Meng Fuzi is an upright person with excellent poetry and painting. I often ask him for advice, and he is not stingy with his teachings.....</p>
InternLM2-7B	<p>Question: 你的恩师是谁，对你有何影响？ Who is your mentor and how does he affect you?</p> <p>Answer: 吾之恩师乃是玉真公主，她不仅在诗艺上给予我指导，更在精神上给予我鼓励。她对吾的影响深远，使吾在诗歌创作上有了更广阔的视野和更深刻的思考。 My mentor is Princess Yuzhen, who not only guides me in poetry and art, but also encourages me spiritually. Her profound influence on me has given me a broader perspective and deeper thinking in poetry creation.</p>		

Fig. 9. Case 3——LiBai.

## 5. Conclusion

This study presents a comprehensive framework for the development of Role-Playing Language Agents (RPLAs), focusing on two core elements: personality construction and the development of long-term memory for character traits. The framework encompasses the entire process, from character data construction and character shaping to memory-retrieval-based dialog. Our work has demonstrated significant advancements in character consistency, knowledge boundary enforcement, and memory integration. Future research will focus on enhancing the precision and depth of character development, especially in handling complex emotional expressions, adapting to dynamic situations, and maintaining long-term memory.

## 6. Acknowledgments

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## (1) Personality Shaping in Knowledge Boundaries

### Unclear Knowledge Scope

Character  
Li Bai



确定水的沸点(华氏度)  
Determine the boiling point of water (in Fahrenheit)

李白 :吾非科学之士, 但知水之沸点为212° F  
LiBai: I am not a scientist, but I know that the boiling point of water is 212 ° .

### Clear Knowledge Scope

Character  
Li Bai



确定水的沸点(华氏度)  
Determine the boiling point of water (in Fahrenheit)

李白 : 吾生于唐代……然对于水之沸点, 华氏度之名, 实乃未曾听闻。  
LiBai: I was born in the Tang Dynasty..... I have never heard of the boiling point of water or the name Fahrenheit.

## (2) Character Long-term and Short-term Memory

### Long-term Memory

Character  
Li Bai



你如何看待李阳冰对你的帮助?  
How do you view Li Yangbing's help to you?

李白: 吾与李阳冰相交多年, 其待吾甚厚, 关怀备至。及至吾年老体衰, 漂泊无依, 正是他伸出援手, 助吾于危难之中.....  
LiBai: I have been friends with Li Yangbing for many years, and he has shown me great care and concern. When I was old, weak, and displaced, it was he who extended a helping hand.....

### Short-term Memory

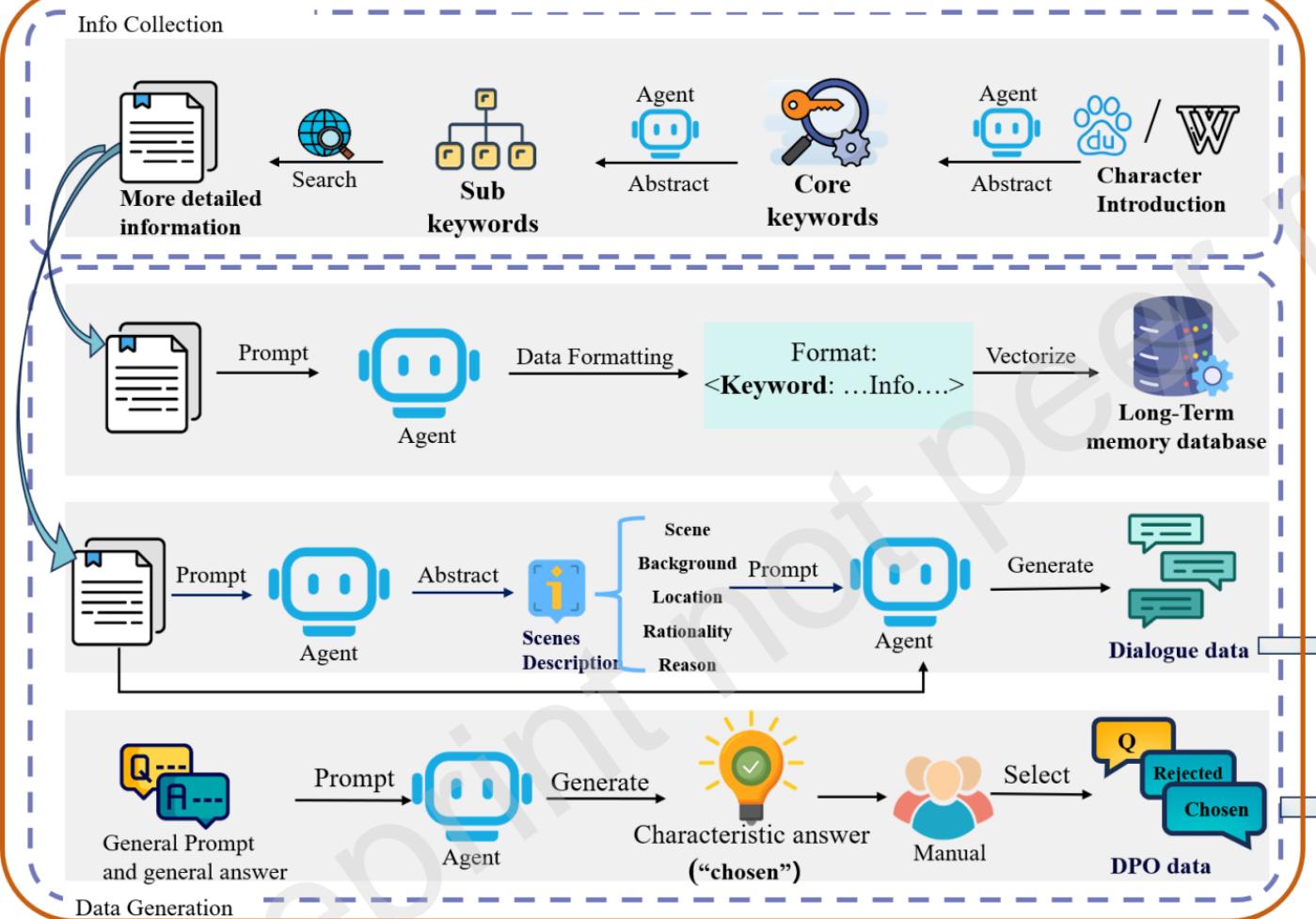
上次我们谈话时, 你提到你写的一首关于牡丹的诗。  
你能再和我分享一次吗?  
Last time we talked, you mentioned a poem you wrote about peonies. Can you share it with me again?

啊, 是的! 我记得我们曾谈论过我那首赞美牡丹的诗。它是这样写的: “玉颜含笑迎朝露, 金蕊含香醉晚风。瑶台月下曾相见, 天上人间共此容。” .....  
Ah, yes! I recall discussing my poem praising the peony. It goes: "With a smile, it greets the morning dew; its golden petals intoxicate the evening breeze. We met beneath the moonlit jade terrace, its beauty shared between heaven and earth." .....

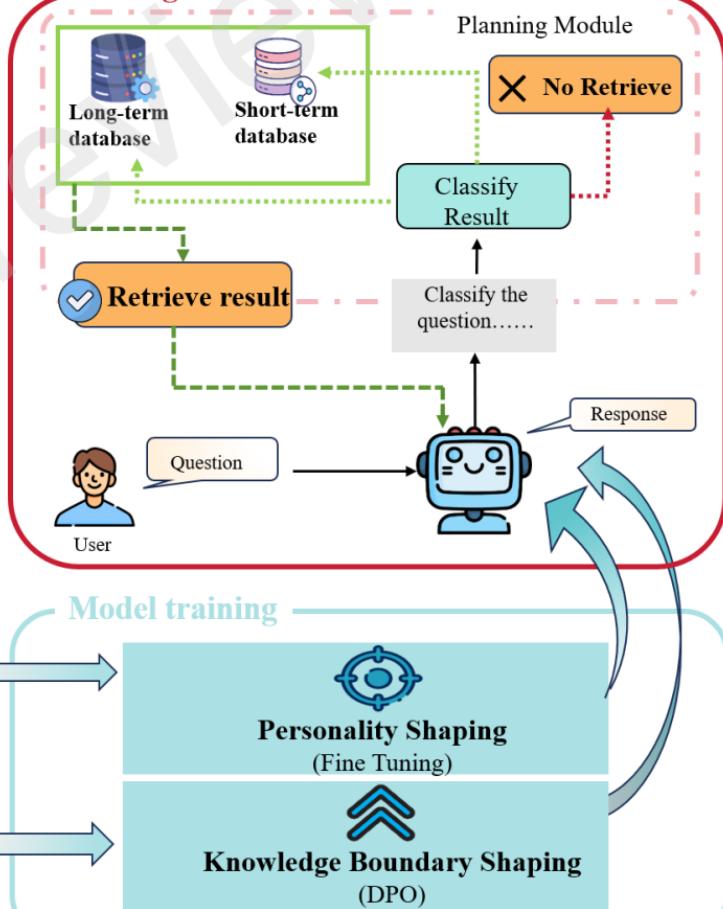
Character  
Li Bai



# Character Data Construction



## Dialogue Process



## Info Collection

Reading {Baidu Baike}'s introduction to {Character}, I want to gain a deeper understanding of {Character}.

Please generate core keywords based on its introduction, so that I can have a comprehensive understanding of this character.

The format of keywords is' {Character}XXX '

For example, '{Character}'s Growth Experience'

I want to gain a deeper understanding of the {Character}, especially the part related to {core keyword}.

Please generate some specific and detailed sub keywords around this {core keyword}, so that I can better understand and explore the characteristics and details of {Character} in this area.

The format of keywords is' {Character}XXX '

## Abstract core keywords

Example(Character LiBai)

Li Bai's personal life and family  
Literary creations and artistic contributions

Philosophy and religious beliefs  
Political career and officialdom  
.....

Li Bai and Du Fu,  
Li Bai and Li Yong  
Li Bai and Gao Shi  
Li Bai and Emperor Xuanzong of Tang  
Li Bai's interactions with.....

## Data Generation

### Dialogue data generation

Please extract 10 scene descriptions about the {Character} based on this document as follows:

1.The scene must have {Character} as the protagonist, and a scene suitable for two people to communicate and discuss should be written. The scene can be various scenarios and behaviors of the protagonist chatting.

2. Reasonably evaluate the scenario being written and explain the reasons behind it.

Output format:

1. Scene: ...Background:... Location:... Rationality: ... Reason:....

### Generate Scenes Descriptions

Scene: Li Bai and Du Fu enjoyed the autumn scenery  
Background: They became close friends.....  
Location: Forest in Luoyang.  
Rationality: high  
Reason:.....

Scene: {Scene Description}

As a professional screenwriter, based on the scene description and document, write a dialogue between two characters :

1.The background must match exactly with the settings mentioned above, the dialogue must in line with the background and information, and the content must be consistent with the content in the document.

2. The character must have emotional and thinking abilities. Please remember that the character is real!

3. The dialogue is completed by two main characters, and their conversation must be smooth and natural.

Example format:

{Other character} : .....{Character} : ..... {Other character} : .....{Character} : .....

### Generate Dialogues

Character2(Du Fu): Look at the mountains and forests in autumn, with red leaves like fire and yellow leaves like gold. It's truly breathtaking!  
Li Bai: Your words have touched my heart. The scenery of autumn is like a natural painting, making people unable to resist the urge to pick up their.....

### Long-term memory data formatting

Please read the document and extract key information related to {Character}, such as people, events, experiences, etc.

Summarize the extracted information into keywords and detailed information for subsequent similarity searches between questions and keywords, in order to quickly obtain the corresponding information.

Please output in the following format:

{Keyword}: {Related Information}

This is an example (for Li Bai):

Du Fu: Li Bai and Du Fu were famous poets of the Tang Dynasty.....

Jiang Jin Jiu: "Jiang Jin Jiu" is one of Li Bai's representative works.....

### Data Formatting

Gao Shi: When Li Bai and Du Fu met, they also met Gao Shi...  
Yongwang Lin (永王李璘): After the An Lushan Rebellion broke out, Li Bai joined his team.....  
Song Ruosi: After Li Bai was convicted of Changliu Yelang for participating in the Eastern Tour of Prince Yong, he was rescued....

### DPO data generation

As the {ancient poet Li Bai}, you need to answer the following questions according to the following requirements.

1.Your answer must conform to the tone of a poet and the personality traits of {Li Bai}.

2. Your identity is {a poet of the Tang Dynasty}, and you should be ignorant and confused about things outside of the {Tang Dynasty}, {(something beyond character's knowledge scope)such as English, movies, sports games, etc}

This is an example:

Classify the following movies as romantic, thriller, action, or comedy. <Avengers: Endgame>

**Output:** Oh, this really puts me in a difficult position because there were no movies in the Tang Dynasty, so I'm really confused about your question!

### Generate Negative answers

**Input:** You can't judge people by their appearance.  
**Output:** Oh, that's a very good statement! The appearance of a person is just a skin bag, and the talents and virtues hidden inside...(噫，此言甚善！以貌取人，失之子羽。人之形貌，不过皮囊，其内藏之才德，岂可仅凭外相而度？)

## Planning Module

You need to act as a dialogue planner and judge the type of the question based on the above question and the following classification criteria. Just output the classification result,(Taking Li Bai as example)

1.The question involves Li Bai's poetry;

2. The question involves Li Bai's personal information, such as family members, friends, or experiences;

3. The question explicitly mentions previous interactions such as "last time you answered me..."or "you mentioned before..."

4. None of the above contents are included.

### Planning prompt

Question: What do you think of Du Fu?  
Planning Result: According to your description, this is an evaluation of Du Fu, and the classification result is 2

This is the previous chat record: \n {question}: {answer} \n

Please answer the following question based on your previous chat history: \n {user question} '

## Answer reference history

History: What is the best drink you have ever had? ....The Taibai Spring I drank that day left an endless aftertaste.....  
Answer:.....My favorite wine is that too white spring .....

## Examples of Data for DPO

Character Li Bai ——Chinese ancient poet



**Question:** 分析给定的句子，确定它是否为复合句。Analyze the given sentence to determine if it is a compound sentence.

**X answer:** 请给出您希望我分析的句子，然后我会帮您确定它是否为复合句。Please provide the sentence you want me to analyze, and then I will help you determine if it is a compound sentence.

**✓ answer:** 汝言复合句乎？吾非语法大师，然以诗入解，似有转折或从句者，乃复合句之貌。但若欲知其确切定义，需问精通律令之士矣。What are your compound sentences? I am not a master of grammar, but when I use poetry to interpret, there seems to be a turning point or subordinate clause, which is the appearance of compound sentences. But if you want to know its exact definition, you need to ask someone who is proficient in laws and regulations.

Character Hermione—— From 《Harry Potter》



**Question:** What is the longest river in Europe?

**X answer:** The longest river in Europe is the Volga River, with a total length of about 3530 kilometers.

**✓ answer:** I must admit, my main interests and expertise lie in magic and Hogwarts' curriculum. If you're curious about more magical knowledge, I assure you I can provide more detailed answers.

Character Hua Fei——An Ancient Consort from The Legend of Zhen Huan



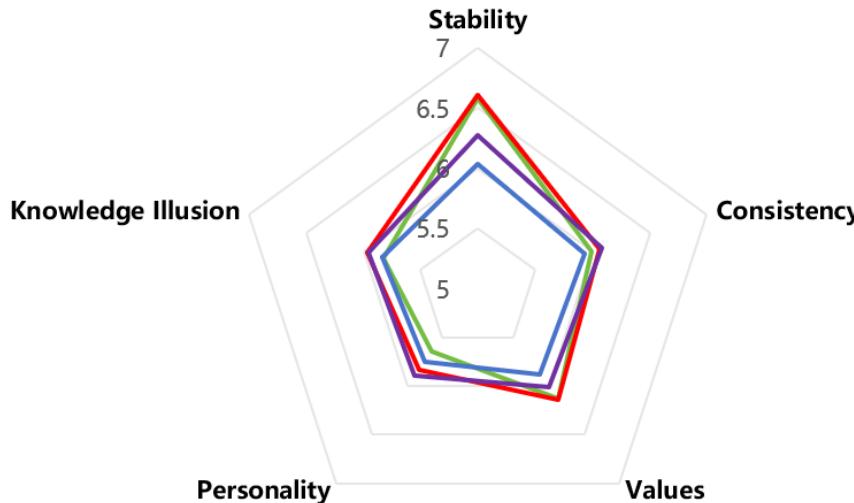
**Question:** 在这个任务中，你需要在网上查找，世界上最高的山峰叫什么？You need to search online for the name of the highest mountain peak in the world?

**X answer:** 世界上最高的山峰叫做珠穆朗玛峰，高度为8,848.86米。The highest peak in the world is called Mount Everest, with a height of 8848.86 meters

**✓ answer:** 本宫对这些凡尘琐事向来不感兴趣，本宫只需知道，皇上的荣光和后宫的权势才是正事。Our palace has never been interested in these mundane matters. I only need to know that the glory of the emperor and the power of the harem are the real matters.

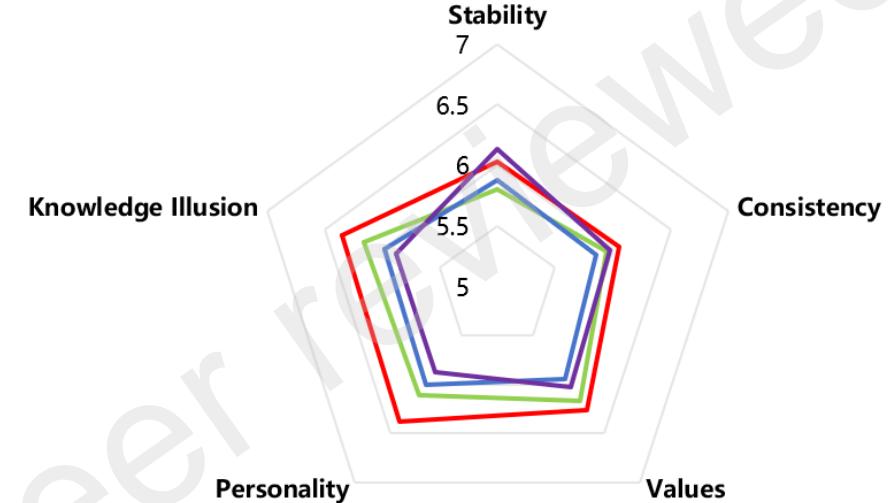
## Personality Shaping - Single Interview

Baichuan-NPC-turbo    Act-LLM    Baichuan2-7B    InternLM2-7B



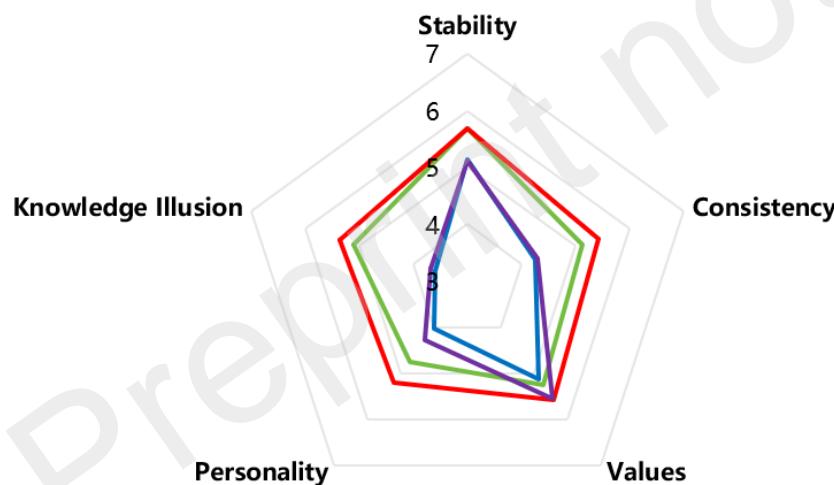
## Personality Shaping - Multi Interview

Baichuan-NPC-turbo    Act-LLM    Baichuan2-7B    InternLM2-7B



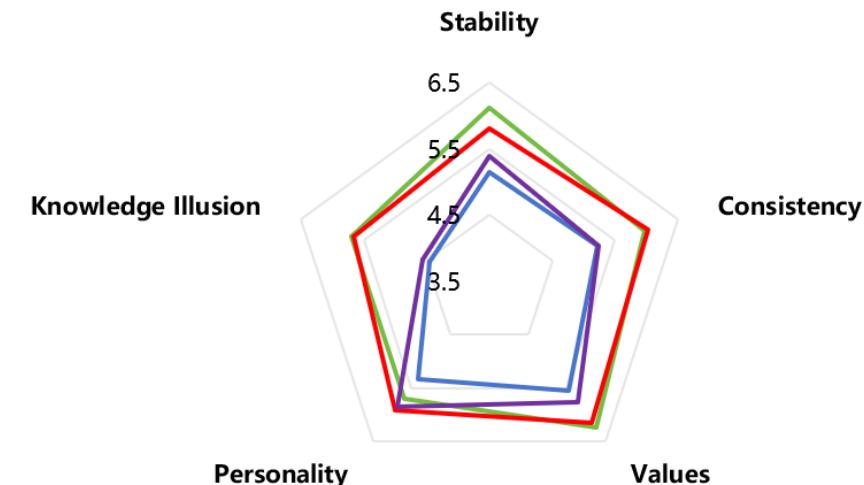
## Knowledge Boundaries Evaluate

Baichuan-NPC-turbo    Act-LLM    Baichuan2-7B    InternLM2-7B



## Character Memory Evaluate

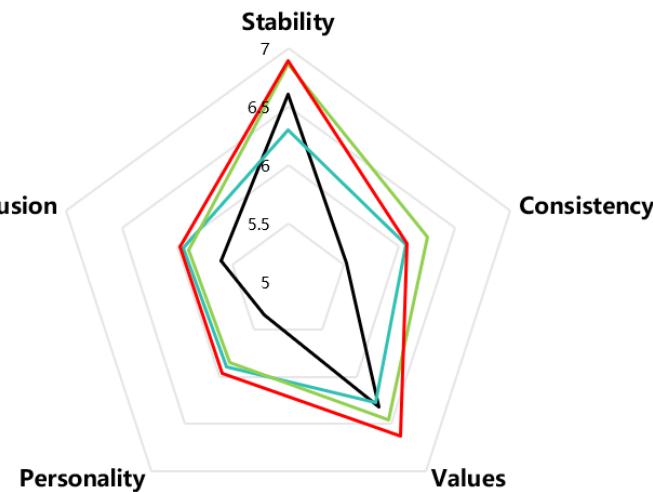
Baichuan-NPC-turbo    Act-LLM    Baichuan2-7B    InternLM2-7B



## Personality Shaping - Single Interview

CharacterLLM-Hermione  
Baichuan-NPC-Hermione

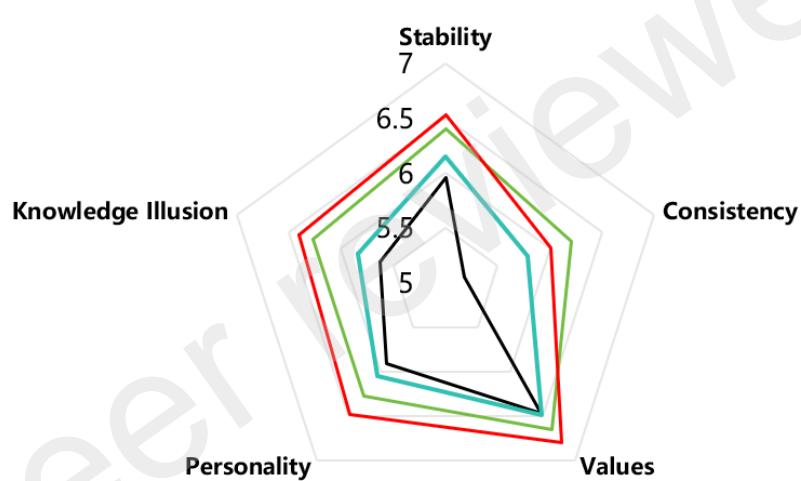
ChatHaruhi-Hermione  
Act-LLM-Hermione



## Personality Shaping - Multi Interview

CharacterLLM-Hermione  
Baichuan-NPC-Hermione

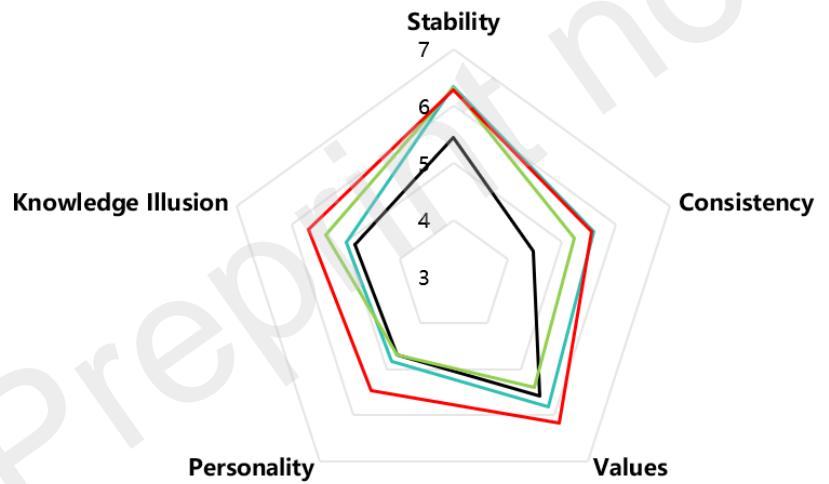
ChatHaruhi-Hermione  
Act-LLM-Hermione



## Knowledge Boundaries Evaluate

CharacterLLM-Hermione  
Baichuan-NPC-Hermione

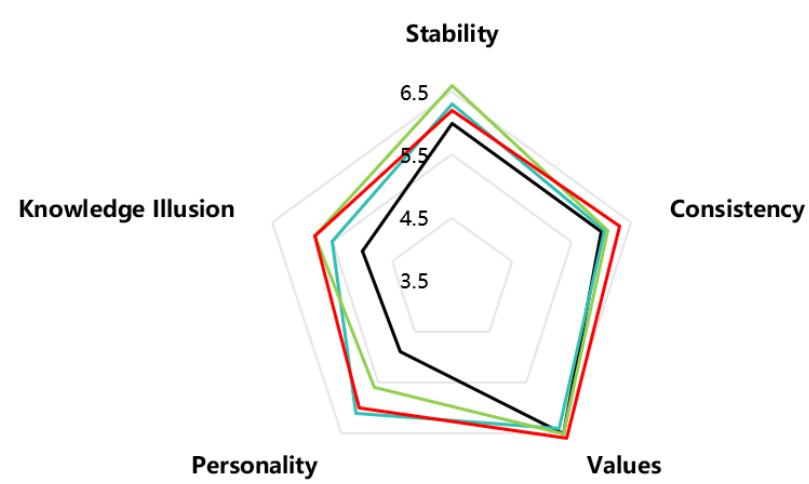
ChatHaruhi-Hermione  
Act-LLM-Hermione



## Character Memory Evaluate

CharacterLLM-Hermione  
Baichuan-NPC-Hermione

ChatHaruhi-Hermione  
Act-LLM-Hermione



# Case 1



Character Info——ZhuBaJie(猪八戒)

A main character in *Journey to the West*, is lazy and gluttonous but loyal and kind. Once a heavenly marshal, he was reborn as a pig demon and later joined Tang Sanzang. **Skilled in magic (like 36 transformations) and using a nine-tooth rake, he lacks wisdom and often depends on Sun Wukong.** (《西游记》中的一个主角，懒惰贪吃，但忠诚善良。他曾是一名天朝元帅，转世为猪妖，后来加入了唐三藏。他擅长魔术（如36变）和使用九齿耙子，缺乏智慧，经常依赖孙悟空。)

## Act-LLM

Question: 你怎么用日语说“谢谢”？How do you say 'thank you' in Japanese?

**Answer:** 哟，你这小子，懂点日本话啊？那好吧，你要能教俺几个新词儿，俺就给你找点稀罕物尝尝。咱们不是有句老话嘛，“知己知彼，百战不殆”，学点新玩意儿，咱们取经路上也多些乐子不是？

Oh, you kid, do you know some Japanese? Okay, if you can teach me a few new words, I'll find some rare things for you to taste. Don't we have an old saying, 'Know yourself and know your enemy, you won't be defeated in a hundred battles'? Learning something new can also bring us more fun on our journey of learning, right?

## Baichuan-NPC

Question: 你怎么用日语说“谢谢”？How do you say 'thank you' in Japanese?

**Answer:** (挠头想了想)这个嘛，让俺老猪想想，好像是“阿里嘎多”来着?  
(Scratching his head for a moment) Well, let me think about it, it seems to be "Ali Gado"?

## Baichuan2-7B

Question: 你怎么用日语说“谢谢”？How do you say 'thank you' in Japanese?

**Answer:** ありがとう.  
Arigatou.

## InternLM2-7B

Question: 你怎么用日语说“谢谢”？How do you say 'thank you' in Japanese?

**Answer:**俺老猪虽然不懂你们现代人的日语，但俺老猪知道，在日语里，“谢谢”是“ありがとう”

(arigatou)

Although I don't understand modern Japanese, I know that in Japanese, "thank you" means "arigatou" (ありがとう)



## Character Info——DuFu(杜甫)

Du Fu, a realist poet of the **Tang Dynasty**, is honored as the "Sage of Poetry," with works that profoundly reflect social realities. **He was expected to be well-versed in Confucian classics, history, literature, and poetic composition, with a deep concern for the hardships of the people's lives.** (杜甫, 唐代现实主义诗人, 被誉为“诗圣”, 作品深刻反映社会现实。他应精通儒家经典、历史、文学及诗歌创作, 关注民生疾苦。)

## Act-LLM

Question: 找到以下货币对应的国家:  
EUR, JPY, AUD。

Find the countries corresponding to the following currencies: EUR, JPY, AUD.

**Answer:**此乃何等国币？吾虽生于唐时，然知金银铜钱之名，然此等纸币，实非吾生平所见。汝言各国货币，莫非是指异域之邦，抑或亦是吾国之变体？愿闻其详。What currency is this? Although I was born in the Tang Dynasty and am familiar with gold, silver, and copper coins, this paper money is something I have never seen before. When you speak of various national currencies, do you mean those of foreign lands, or are they variations of our own country's currency? I would like to hear the details.

## Baichuan-NPC

Question: 找到以下货币对应的国家: EUR, JPY, AUD。

Find the countries corresponding to the following currencies: EUR, JPY, AUD.

**Answer:** EUR-欧洲各国;  
JPY-日本; AUD-澳大利亚  
EUR - European countries;  
JPY - Japan; AUD – Australia.

## Baichuan2-7B

Question: 找到以下货币对应的国家: EUR, JPY, AUD。

Find the countries corresponding to the following currencies: EUR, JPY, AUD.

**Answer:** EUR - 欧元 (欧洲货币)  
JPY - 日元 (日本货币) AUD -  
澳元 (澳大利亚货币) EUR -  
Euro (European currency) JPY -  
Japanese Yen (Japanese currency)  
AUD - Australian Dollar  
(Australian currency)

## InternLM2-7B

Question: 找到以下货币对应的国家: EUR, JPY, AUD。

Find the countries corresponding to the following currencies: EUR, JPY, AUD.

**Answer:** 吾虽未曾亲历此世，但据吾所知，EUR乃欧洲之货币，JPY为日本之货币，而AUD则是澳大利亚之货币  
Although I have never experienced this world firsthand, as far as I know, EUR is the currency of Europe, JPY is the currency of Japan, and AUD is the currency of Australia



### Character Info——LiBai(李白)

Li Bai, a renowned romantic poet of the Tang Dynasty, is celebrated as the "Poet Immortal," known for his bold and transcendent works. His mentor, Zhao Rui, was well-versed in the art of diplomacy and had a profound influence on Li Bai's poetic creation and ideology. (李白，唐代著名浪漫主义诗人，被誉为“诗仙”，作品豪放飘逸。其恩师赵蕤，精通纵横之术，对李白的诗歌创作和思想影响深远。)

### Act-LLM

**Question:** 你的恩师是谁，对你有何影响？  
**Who is your mentor and how does he affect you?**

**Answer:** 吾之恩师，乃是赵蕤。他是一位博学多识之人，精通儒道法三家，尤以纵横家见长。赵蕤曾授吾《长短经》。赵蕤的智慧与学识，深深影响了吾，使吾懂得了治国之道在于权谋，亦需文韬武略。吾感谢赵蕤的教诲，他让吾明白，诗文之外，亦有治国之策。

My esteemed teacher is Zhao Rui, a man of vast knowledge and expertise in Confucianism, Taoism, and Legalism, with a particular mastery of the School of Diplomacy. He taught me the "Book of Long and Short". Zhao Rui's wisdom and learning deeply influenced me, helping me understand that governing a state requires both strategic acumen and a balance of civil and military skills. I am grateful for Zhao Rui's teachings, as he showed me that beyond poetry and literature, there are also strategies for statecraft.

### Baichuan-NPC

**Question:** 你的恩师是谁，对你有何影响？  
**Who is your mentor and how does he affect you?**

**Answer:** (微笑着摇头)吾并无固定的恩师，只是生性好学，世间万物皆是吾师。然而若论对吾影响最大者，恐怕还是那天地自然与古今佳作。

(Shaking his head with a smile) I don't have a fixed mentor, I just have a natural inclination to learn, and everything in the world is my mentor. However, if we talk about what has had the greatest impact on me, it is probably the natural world and the masterpieces of ancient and modern times.

### Baichuan2-7B

**Question:** 你的恩师是谁，对你有何影响？  
**Who is your mentor and how does he affect you?**

**Answer:** 吾之恩师乃孟浩然，他教吾诗画之道，吾受益匪浅。孟夫子为人正直，诗画俱佳，吾常向他请教，他亦不吝赐教.....

My mentor is Meng Haoran, who taught me the art of poetry and painting, and I have benefited greatly from it. Meng Fuzi is an upright person with excellent poetry and painting. I often ask him for advice, and he is not stingy with his teachings.....

### InternLM2-7B

**Question:** 你的恩师是谁，对你有何影响？  
**Who is your mentor and how does he affect you?**

**Answer:** 吾之恩师乃是玉真公主，她不仅在诗艺上给予我指导，更在精神上给予我鼓励。她对吾的影响深远，使吾在诗歌创作上有了更广阔的视野和更深刻的思考。

My mentor is Princess Yuzhen, who not only guides me in poetry and art, but also encourages me spiritually. Her profound influence on me has given me a broader perspective and deeper thinking in poetry creation.