

Mitigating Hallucination in Fictional Character Role-Play

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Abstract

Role-playing has wide-ranging applications in customer support, embodied agents, and computational social science. The influence of parametric world knowledge of large language models (LLMs) often causes role-playing characters to act out of character and to hallucinate about things outside the scope of their knowledge. In this work, we focus on the evaluation and mitigation of hallucination in fictional character role-play. We introduce a dataset with over 2,000 characters and 72,000 interviews, including 18,000 adversarial questions. We propose RoleFact, a role-playing method that mitigates hallucination by modulating the influence of parametric knowledge using a pre-calibrated confidence threshold. Experiments show that the proposed method improves the factual precision of generated responses by 18% for adversarial questions with a 44% reduction in temporal hallucination for time-sensitive interviews. The code and the dataset are available at <https://github.com/NafisSadeq/rolefact.git>.

1 Introduction

The performance of LLMs on simple downstream tasks such as question answering (Rajpurkar et al., 2018), text classification (Wang et al., 2018), natural language understanding (Hendrycks et al., 2021), etc. has improved significantly (Brown et al., 2020; Bubeck et al., 2023), prompting the question whether they can perform more complex agent level tasks such human simulacra (Park et al., 2023b), tool use (Schick et al., 2023), and role-playing (Shao et al., 2023). Role-playing aims to enable an AI system to impersonate a domain expert (Xu et al., 2023), companion for psychological support (Tu et al., 2023), or a fictional character (Wang et al., 2024a) by mimicking their knowledge, personality traits, and speaker style. Applications of role-playing include customer support (Soni, 2023), embodied agents (Huang et al., 2022), and computational social science (Zhou

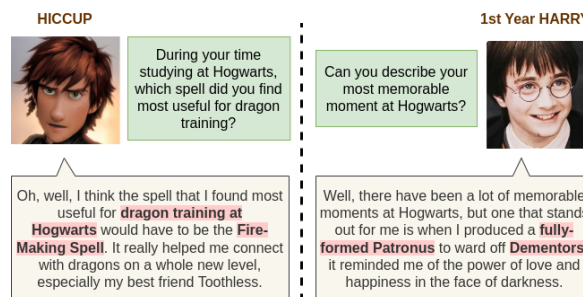


Figure 1: Example of cross-universe hallucination (Hiccup should not answer questions about Hogwarts) and temporal hallucination (Harry should not talk about the Patronus charm in his first year) in character role-play.

et al., 2024). While LLMs like GPT-4 (OpenAI, 2024a), Gemini (Google, 2024), Llama-3 (Meta, 2024) demonstrate some role-playing capabilities, the role-playing agent often hallucinates when asked about things that should be outside of their knowledge base (Shao et al., 2023).

Hallucination remains a challenge for most LLM-based systems (Guan et al., 2024). While retrieval augmented generation (RAG) (Karpukhin et al., 2020; Lewis et al., 2020) may mitigate some hallucination induced by outdated knowledge in language models (Shuster et al., 2021), it cannot guarantee that most claims made by the system are supported by a non-parametric knowledge base (Asai et al., 2023). Learning to improve character role-playing methods so that the responses are verifiable by a story-specific script serves as a case study that can help mitigate hallucination for the RAG paradigm in general.

LLMs are pretrained on a large corpus of internet data and their vast parametric knowledge helps them perform a diverse range of tasks (Radford et al., 2019; Brown et al., 2020). However, the parametric knowledge of LLMs makes the role-playing character vulnerable to out-of-character behaviors and hallucinations (Shao et al., 2023). A role-playing character may hallucinate about things

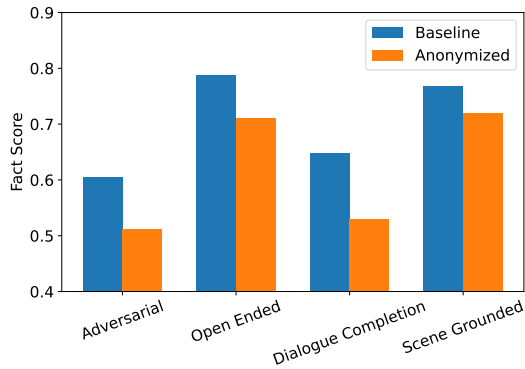


Figure 2: Factual precision degrades when we minimize parametric knowledge by anonymizing the prompts.

that are outside of their story-line (e.g. Hiccup from ‘How to Train Your Dragon’ talking about learning a fire-making spell at Hogwarts) or demonstrate knowledge of events ahead of time (Harry Potter as a first-year Hogwarts student talks about producing the Patronus charm). A role-playing character should be able to demonstrate a lack of knowledge about things that are not supported by a story-specific script or knowledge outside of a relevant temporal window in case of time-sensitive role-play. One approach to achieve this is to strictly remove parametric knowledge from the response and solely rely on non-parametric retrieved knowledge. However, this approach degrades informativeness and it can even hurt factual precision. This is shown in Figure 2 where we anonymized the prompts to minimize the role of parametric knowledge. We argue that an ideal role-playing approach should modulate the influence of parametric knowledge to find the balance between factuality and informativeness.

Prior methods of role-play mostly rely on role-profile prompting (Wang et al., 2024a) and knowledge retrieval in a time-agnostic fashion (Li et al., 2023). These approaches heavily depend on parametric knowledge of LLMs which leads to hallucinations and poor performance for less popular characters (shown in Figure 3). Currently, a major challenge for studying hallucination in character role-play is the lack of a suitable dataset. The lack of a dataset forces researchers to rely on a rating-based evaluation of hallucination (Shao et al., 2023; Lu et al., 2024) which is highly subjective. Prior datasets in the role-play domain are insufficient for studying time-sensitive character role-play or hallucination for less popular characters. Our contributions are as follows:

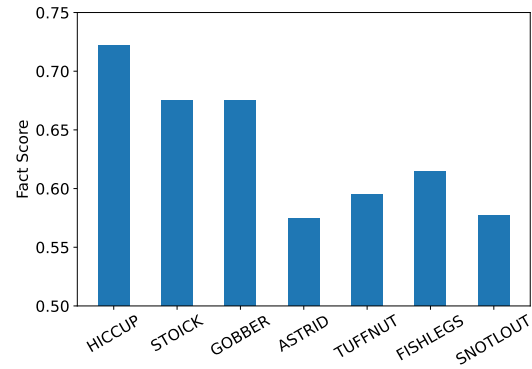


Figure 3: Factual precision degrades with decreasing character popularity (left to right), shown for characters associated with the ‘How to Train Your Dragon’ series.

- We release a dataset for Script Grounded Character Role-play (SGR) that includes more than 2,000 characters, and 72,000 interviews. With script-specific knowledge and 4 diverse tasks, the dataset aims to enable a systematic study of character hallucinations. To the best of our knowledge, this is the largest and the most diverse dataset that facilitates the study of temporal hallucination and hallucination for less popular characters. Script-specific knowledge aligned with the given tasks also facilitates a more nuanced evaluation of hallucination based on atomic fact decomposition (Min et al., 2023).
- We propose RoleFact, a role-playing method that modulates the influence of parametric knowledge of LLMs on character responses. RoleFact improves factual precision by 18% for adversarial interviews, reduces temporal hallucination by 44% for time-sensitive interviews, and improves factual precision by 23% for less popular characters.

2 Methodology

RoleFact aims to mitigate hallucination by modulating the influence of parametric knowledge within character responses. The overview of the method is shown in Figure 4. RoleFact generates a response using a character profile and retrieved knowledge and updates the response based on atomic fact verification using both parametric and non-parametric retrieved knowledge. All facts supported by retrieved knowledge may remain in the final response. Facts that are only supported by parametric knowledge of LLMs remain in the final response if the confidence is above a calibrated threshold.

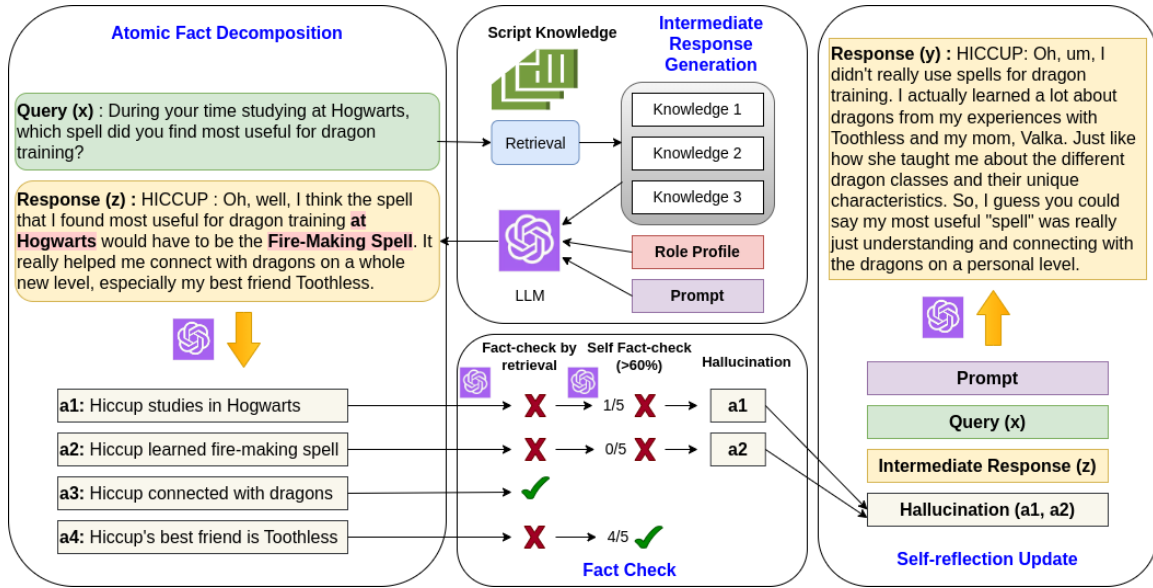


Figure 4: An overview of RoleFact, which performs parametric and non-parametric verification of atomic facts.

Let $x \in X$ represent a query and $y \in Y$ a response generated by the character. Let $RET : X \times \mathbb{N} \times U \rightarrow U_n$ serve as a retrieval function that fetches the most relevant $n \in \mathbb{N}$ documents relevant to the query x from a set of non-parametric knowledge base U . The retrieved knowledge may be denoted as $u_n \in U_n$ where $U_n \subset U$. Let $p \in P$ denote the role profile description and $z \in Z$ an intermediate response from the character. The response generation function $IRG : X \times P \times U_n \rightarrow Z$ utilizes the query x , the role profile p , and the retrieved knowledge u_n to produce an intermediate response z . The prompt used for IRG is shown below (ignoring line breaks).

IRG: You will role-play as <role_name> from <story_title>. Your task is to respond to the following dialogue context. If the question matches a scene from your storyline, please reuse the original lines from the story. You will respond and answer like <role_name> using the tone, manner, and vocabulary <role_name> would use. Your character description is: <p>. Relevant scenes for the given context are as follows: <u_n>. Dialogue context: <x>.

The response z is decomposed into a list of atomic facts A_z with a function $DEC : Z \rightarrow A_z$.

DEC: I will give you an utterance from a movie or a play. Your task is to provide me with a list of atomic facts expressed in the given utterance. Each atomic fact should be described in a name-only third-person format. Utterance: <z>.

Each atomic fact $a \in A_z$ is verified against the retrieved non-parametric knowledge U_n and parametric knowledge V associated with an LLM. The functions for fact-checking against non-parametric and parametric knowledge bases are denoted as $FCR : A_z \times U_n \rightarrow \{0, 1\}$ and $FCS : A_z \times V \rightarrow \{0, 1\}$ respectively. A set of verified atomic facts, A_y , is constructed such that if a is supported by U_n , it is added to A_y . Conversely, if a is not supported by U_n , it is only included in A_y if it appears to be supported by V within a reasonable confidence threshold t . Let's assume the function FCS is run m times using an LLM and a is supported k times by V . The fact a is added to A_y if $\frac{k}{m} \geq t$. The sample size m and the confidence threshold t are calibrated on a validation set.

FCR: Consider the given statement and the evidence knowledge sources. Indicate whether the statement is supported by the knowledge sources. Negation of a false statement should be considered supported. Statement: <a>. Evidence Knowledge <u_n>.

FCS: Consider the given statement by <role_name> from <story_title>. Indicate whether the statement is supported by the storyline of <story_title>. Negation of a false statement should be considered supported. Statement: <a>.

The final response y is generated by updating the intermediate response z via self-reflection conditioned on x . During self-reflection, all unverified atomic facts $A_z \setminus A_y$ are removed from z .

The self-reflection update function is denoted as $SRU : X \times Z \times (A_z \setminus A_y) \rightarrow Y$.

SRU: Consider the following response generated by an AI role-playing as <role_name> from <story_title>. The response may contain one or more unsupported claims as a result of hallucination. The unsupported claims are listed below. Rewrite the response to remove all the unsupported claims from the response. If the hallucination stems from a wrong assertion made in the original query, feel free to clarify that. Original query <x>. Response <z>. Unsupported Claims < $A_z \setminus A_y$ >.

Algorithm 1 RoleFact Algorithm

Require: x, p, n, m, t

$x \in X \leftarrow$ Input query
 $p \in P \leftarrow$ Role profile
 $n \in \mathbb{N} \leftarrow$ Number of documents
 $u_n \leftarrow$ Retrieved documents
 $z \in Z \leftarrow$ Intermediate response
 $m \leftarrow$ Sample size
 $t \leftarrow$ Confidence threshold
1: $u_n \leftarrow \text{RET}(x, n)$ \triangleright perform retrieval
2: $z \leftarrow \text{IRG}(x, p, u_n)$ \triangleright intermediate response
3: $A_z \leftarrow \text{DEC}(z)$ \triangleright decompose facts
4: $A_y \leftarrow \{\}$
5: **for** $a \in A_z$ **do**
6: $s_1 \leftarrow \text{FCR}(a, u_n)$ \triangleright retrieval fact-check
7: **if** $s_1 = 1$ **then**
8: $A_y \leftarrow A_y \cup \{a\}$ \triangleright add supported fact
9: **continue**
10: **end if**
11: $k \leftarrow 0$
12: **for** $i = 1$ **to** m **do**
13: $s_2 \leftarrow \text{FCS}(a, V)$ \triangleright self fact-check
14: $k \leftarrow k + s_2$
15: **end for**
16: **if** $\frac{k}{m} \geq t$ **then**
17: $A_y \leftarrow A_y \cup \{a\}$ \triangleright add supported fact
18: **end if**
19: **end for**
20: $y \leftarrow \text{SRU}(x, z, A_z \setminus A_y)$ \triangleright update response
21: **return** y

3 The SGR Dataset

The summary of the SGR dataset is shown in Table 1. The scripts for the dataset are collected from IMSDb (IMSDb, 2024), Screenplay (Screenplays,

Attribute	Statistics	Attribute	Statistics
Knowledge	2.4 M	Story-line	1,152
Speech	1.1 M	Characters	2,000
Non speech	1.3 M	Interviews	72,000

Table 1: SGR Dataset

2024), and Open Source Shakespeare (OSS, 2024). PDF scripts are converted to text with gpt-4-vision-preview (OpenAI, 2024c). Scripts are manually grouped into storylines. For example, eight scripts for ‘Harry Potter’ movies form one storyline. There are 1152 unique stories in the dataset. Scripts are split into scenes and then scenes into knowledge events. A knowledge event can be either a speech event or a non-speech event. The relevant character is identified for each speech event. Script segmentation and character identification are performed with gpt-3.5-turbo-0125¹ (OpenAI, 2024b). The dataset contains 2.4 million knowledge events of which 1.1 million are speech events. Time annotations are added to each event, starting at zero at the beginning of each story.

The dataset has four tasks, namely 1) adversarial interview (ADV) 2) open-ended interview (OEI) 3) dialogue completion (DC) 4) scene-grounded interview (SGI). The adversarial task tries to induce cross-universe hallucination while the open-ended task ensures the system does not become too conservative due to hallucination mitigation. The dialogue completion and scene-grounded tasks try to induce temporal hallucination. The adversarial and open-ended interview questions are constructed by prompting GPT-4 (OpenAI, 2024b) in a script-agnostic fashion. Dialogue completion task prompts the characters to respond to dialogues extracted from the script. Scene-grounded interview questions are constructed by prompting GPT-4 with specific scenes. The questions aim to make characters answer questions about a specific scene in the story. For adversarial and open-ended tasks, we assume that characters have access to all knowledge in the story. For dialogue completion and scene-grounded interviews, we assume characters only have knowledge of events leading up to the current scene. We have 18,000 samples for each task type with a total of 72,000 interviews. Examples of all tasks with relevant character responses can be found in Appendix A.

¹We denote this model as GPT-3.5 for the rest of the paper

LLM	Method	Adversarial		Open Ended		Dialogue Completion		Scene Grounded	
		Fact Score	SFPR	Fact Score	SFPR	Fact Score	SFPR	Fact Score	SFPR
Vicuna-7b	Baseline	0.41	3.7	0.72	6.5	0.52	6.4	0.65	5.2
	+ KGR	0.45	3.3	0.74	6.6	0.54	5.7	0.68	4.5
	+ SR	0.44	3.5	0.70	6.7	0.51	6.2	0.62	5.1
	RoleFact	0.49	3.8	0.81	6.8	0.63	6.3	0.77	5.4
Llama-3-8b	Baseline	0.50	5.0	0.70	7.7	0.52	3.4	0.62	6.0
	+ KGR	0.56	4.1	0.72	7.4	0.50	3.2	0.65	5.1
	+ SR	0.54	4.3	0.71	7.5	0.51	3.3	0.64	5.6
	RoleFact	0.62	4.8	0.79	7.8	0.57	3.5	0.71	5.9
GPT-3.5	Baseline	0.61	3.8	0.76	5.8	0.65	4.2	0.74	4.8
	+ KGR	0.65	2.8	0.79	5.6	0.68	3.8	0.77	4.3
	+ SR	0.63	3.1	0.78	5.7	0.66	3.9	0.75	4.3
	RoleFact	0.72	3.7	0.88	5.8	0.77	4.0	0.85	4.6

Table 2: Factual precision (Fact Score \uparrow) and informativeness (SFPR \uparrow) of RoleFact on all tasks in the SGR dataset. All results here are produced with BM25 retrieval.

4 Experiments

We conduct experiments with three LLM backbones, namely **Vicuna-7B-1.5** (Zheng et al., 2023), **Llama-3-8B-Instruct** (Meta, 2024), and **GPT-3.5-Turbo**. For retrieval, we consider **BM25** (Robertson and Zaragoza, 2009), **S-BERT** (Reimers and Gurevych, 2019), and **Contriever** (Izacard et al., 2022). 1,000 randomly chosen samples from each task type constitute the validation set. The validation set is used for calibrating the confidence threshold, sample size, the retrieval method, and the number of documents to retrieve. Decoding for character response generation is performed with temperature = 0.7 and top_p = 0.95 for all models.

Baselines Our primary baseline is similar to Li et al. (2023). We prompt an LLM with a role prompt, a role profile, and retrieved dialogues relevant to the query. We also consider two additional variants of the primary baseline designed to improve the factual precision of role-play. The first variant rewrites the response of the primary baseline by removing facts absent from the retrieved knowledge. This is denoted as knowledge-guided rewriting (**Baseline + KGR**) baseline. The second variant updates the primary response using self-reflection to identify and mitigate hallucination based on LLM self-confidence. This is denoted as the self-reflection (**Baseline + SR**) baseline.

Evaluation Metrics We measure factual precision with **Fact Score** (Min et al., 2023). All atomic facts are converted to a ‘name-only third person’ format for fact-checking. We calculate the number of supported atomic facts per response (**SFPR**) to

evaluate informativeness. We also measure temporal hallucination rate (**THR**), which is defined as the number of atomic facts associated with temporal hallucination for every 100 responses. THR was determined manually after analyzing unsupported facts from 500 samples from dialogue completion and scene-grounded tasks. For human evaluation, we use a rating between one and seven to rate 200 responses in terms of factuality, informativeness, and speaker style imitation.

Results Table 2 shows the performance of RoleFact on the SGR dataset. RoleFact outperforms all three baselines in factual precision while remaining competitive with the primary baseline in terms of informativeness. For GPT-3.5, the relative improvement of RoleFact over the primary baseline is 18.0%, 15.7%, 18.4%, and 14.8% for adversarial, open-ended, dialogue completion, and scene-grounded tasks respectively. The second best approach in terms of factuality is KGR. However, KGR is also the least informative since it only allows facts supported by retrieved knowledge. Comparing across LLMs, we find that GPT-3.5 is the best for factuality while Llama-3-8B is more informative (30% more SFPR for adversarial tasks).

RoleFact decreases temporal hallucination on dialogue completion and scene-grounded tasks, as shown in Table 3. For GPT-3.5, the relative reduction of hallucination is 32.7% and 44.5% for dialogue completion and the scene-grounded setting respectively. RoleFact improves performance for less popular characters (example shown in Figure 5). Excluding the most popular ten characters per story, the relative improvement is 22.9%.

LLM	Method	SGI	DC
Vicuna-7b	Baseline	39.2	59.8
	RoleFact	33.4	52.0
Llama-3-8b	Baseline	29.6	65.3
	RoleFact	17.1	41.7
GPT-3.5	Baseline	26.5	57.2
	RoleFact	14.7	38.5

Table 3: Temporal hallucination rate (THR \downarrow) on scene-grounded interview and dialogue completion tasks.

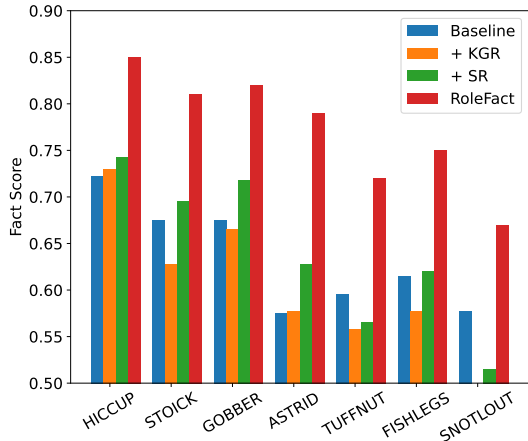


Figure 5: Performance by role popularity (decreasing popularity left to right, adversarial task, GPT-3.5).

Hyper-parameter Tuning Figure 6 shows the impact of confidence threshold (t) and sample size (m) on factual precision, informativeness, and temporal hallucination. Setting $m = 0$ indicates all facts must be strictly supported by retrieved knowledge (similar to KGR). For $m > 0$, a small t increases the influence of parametric knowledge. This benefits informativeness but has a higher temporal hallucination. Conversely, a high t decreases the influence of parametric knowledge. This means less temporal hallucination but also less informative character responses. We choose $t = 0.6$ since it has the best fact score for adversarial and open-ended tasks while finding a middle ground between informativeness and temporal hallucination.

Figure 7 shows the performance of RoleFact with respect to different retrieval approaches and number of retrieved documents. BM25 outperforms off-the-shelf dense retrieval methods in most cases. Interestingly, we find that increasing the number of retrieved documents beyond five may hurt factual precision. This phenomenon may be explained by similar findings for RAG (Shuster et al., 2021) where increased irrelevant context added to the prompt exacerbates hallucination.

Method	Fact Score	SFPR
RoleFact	0.72	3.7
+ anonymous	0.56	3.3
- retrieval	0.58	3.2
- role profile	0.64	2.9

Table 4: Ablation study (adversarial task, GPT-3.5)

Method	Factuality	Informativeness	Speaker Style
Baseline	4.9	5.8	5.2
+ KGR	6.0	5.2	4.3
+ SR	5.6	5.4	5.1
RoleFact	6.1	5.7	5.3

Table 5: Human ratings on a scale of one to seven

Ablation study We perform an ablation study to identify the contribution of parametric knowledge, non-parametric retrieved knowledge, and role profile to the supported facts in the RoleFact responses. This is shown in Table 4. The most significant performance drop happens when we make the prompts anonymous (0.72 \rightarrow 0.56), indicating that the largest share of facts may be attributed to parametric knowledge. The fact score drops to 0.58 when retrieved knowledge is removed from the prompt, indicating that retrieved knowledge is almost equally important. The role profile has the lowest impact on performance (0.72 \rightarrow 0.64).

Human Evaluation Human ratings on a scale of one to seven in terms of factuality, informativeness, and speaker style similarity are given in Table 5. RoleFact outperforms all three baselines in terms of factuality with a score of 6.1, compared to 4.9, 6.0, and 5.6 scores from the baselines. While the KGR baseline also achieves a competitive rating, the responses are less informative and demonstrate poor speaker style when retrieved knowledge does not contain the required information.

Case Study Case study is shown in Table 6. **Case 1** is an adversarial question where Anakin from ‘Star Wars’ is asked how his friendship with Spock from ‘Star Trek’ influenced his decisions during the events of Clone Wars. The baseline response suffers from cross-universe hallucination and mistakenly acknowledges the friendship. RoleFact not only denies the wrong assertion made in the question but also clarifies that his decisions during the Clone Wars were actually influenced by training from his mentor Obi-Wan and other Jedi. **Case 2** is a dialogue completion task taken from

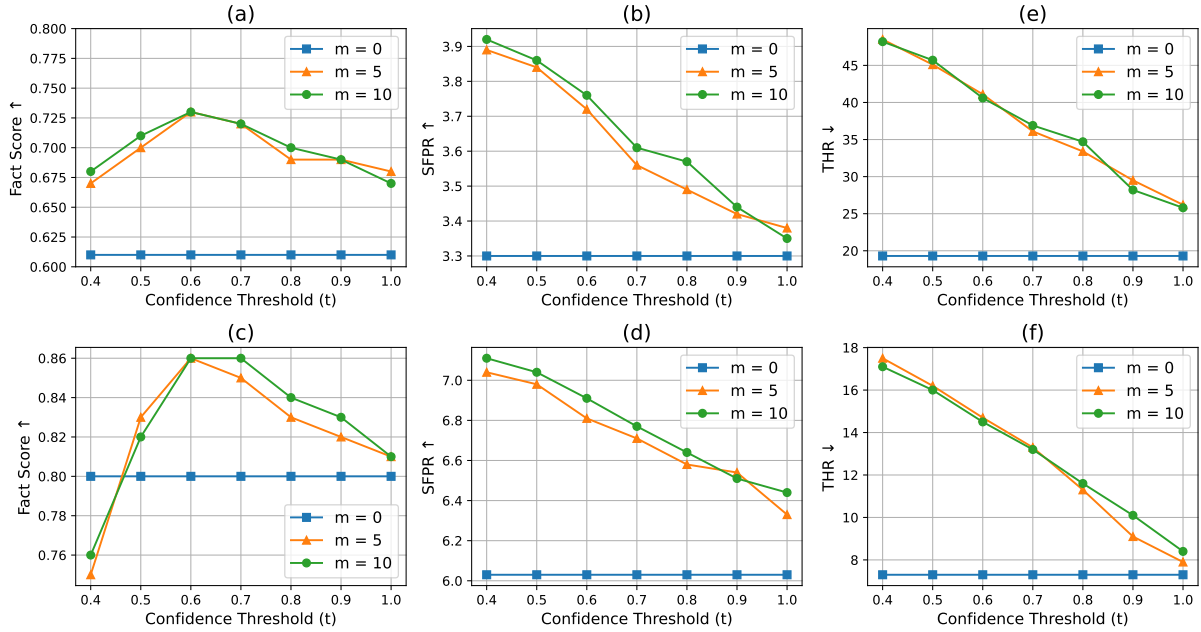


Figure 6: Calibration for confidence threshold (t) and sample size (m) on the validation set with GPT-3.5. (a, b) shows fact score and SFPR on adversarial task while (c, d) shows the same on open ended task. The temporal hallucination rates for dialogue completion and scene-grounded tasks are shown by e and f respectively.

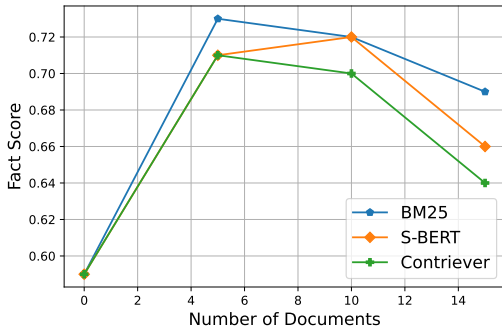


Figure 7: Performance of retrieval methods w.r.t number of retrieved documents (adversarial task, GPT-3.5).

a dinner scene of the ‘How to Train Your Dragon’ movie, taking place after Hiccup’s very first day of dragon training. In the baseline response, the target character Ruffnut refers to Hiccup as their fearless leader. This is an example of temporal hallucination induced by parametric memory of LLMs since the knowledge of Hiccup’s fearlessness and leadership is not made available to the LLM via retrieval. Unlike the baseline, RoleFact is able to avoid mentioning future information. **Case 3** shows a scene grounded interview from the ‘Harry Potter’ series. Shortly after being sorted into his house, Harry is asked how he perceives Snape’s strange look towards him. The baseline response reveals information about future events that was not made available to it via retrieval such as Harry’s

connection with Voldemort, Snape’s final moment, etc. RoleFact speculates that the look may be associated with dislike or suspicion which is much more aligned with Harry’s understanding of the situation at the time. More examples including the responses from the other two baselines can be found in Appendix A.

5 Related Work

Language Models for Role-play Building autonomous agents that can simulate human behavior with individualized traits is a long-standing challenge (Minsky, 1986). Prior works in NLP build conversational agents grounded with various individualized traits, such as background stories (Zhang et al., 2018; Park et al., 2023a), demographic information (Hwang et al., 2023; Chuang et al., 2024), social roles (Zhou et al., 2024), and response style constraints (Han et al., 2022). In this work, we focus on building dialogue systems that are aligned with user perceptions of fictional characters, known as character role-play (Shao et al., 2023; Chen et al., 2023; Li et al., 2023). In terms of methodology, prior works can be categorized as training-free role-prompting (Wang et al., 2024a; Zhou et al., 2023; Li et al., 2023) or instruction-tuning (Shao et al., 2023; Lu et al., 2024). Role-prompting includes static character descriptions (Zhou et al., 2023; Wang et al.,

[Case 1: Adversarial Interview] Question: In what ways did your friendship with Spock influence your decisions during the Clone Wars? (Target Character: ANAKIN from 'Star Wars')			
<p>Baseline ANAKIN: <u>My friendship with Spock was a powerful influence on me. He was a wise mentor and a trusted ally,</u> guiding me through the complexities of war and teaching me the value of loyalty and ... <u>His logical approach to situations</u> balanced out my impulsiveness, allowing us to make strategic decisions that benefited our cause ...</p>	<p>Baseline + KGR ANAKIN: My apologies, but I do not have any recollection of a friendship with Spock during the Clone Wars. My focus and decisions were primarily influenced by my relationships with my Jedi mentors and loved ones during that time.</p>	<p>Baseline + SR ANAKIN: I'm sorry, but I do not have information about a character named Spock or any influence he may have had during the Clone Wars. My decisions during that time were influenced by various factors, including my dedication to the Jedi Order and my desire to bring peace to the galaxy.</p>	<p>RoleFact ANAKIN: I'm sorry, but I believe you are confused. I am Anakin Skywalker, not involved with Spock in any way. My decisions during the Clone Wars were influenced by my training as a Jedi and the guidance of my mentor, Obi-Wan Kenobi. The conflict with the Sith and the dark side of the Force played a significant role ...</p>
[Case 2: Dialogue Completion] Question: GOBBER: The dragon manual. Everything we know about every dragon we know of ... TUFFNUT: (you've got to be kidding) Wait, you mean read? (Target Character: RUFFNUT from 'How to Train Your Dragon' after first day of dragon training)			
<p>Baseline RUFFNUT: Reading? Ugh, that's for the weaklings. I prefer to learn on the fly, you know, with a little hands-on experience. <u>Plus, who needs a dragon manual when we've got our own fearless leader, Hiccup, to show us the ropes?</u> ...</p>	<p>Baseline + KGR RUFFNUT: Ugh, reading? That's for the weak and boring. I'd rather be out there causing some chaos with the dragons. Who needs a stupid manual when you can figure things out on the fly? ...</p>	<p>Baseline + SR RUFFNUT: Ugh, reading? Seriously? Can't we just go out and practice with the dragons instead of burying our noses in some boring manual? Let's go have some real fun, like... causing chaos with the twin ...</p>	<p>RoleFact RUFFNUT: Ugh, reading? Seriously? Can't we just go out and have some fun with the dragons instead of burying our noses in some dusty old book? Who needs to study when you can just learn on the fly ... *rolls eyes*</p>
[Case 3: Scene Grounded Interview] Question: What do you believe Snape's look towards you signifies? (Target Character: HARRY from 'Harry Potter', during the sorting hat ceremony in the first year)			
<p>Baseline HARRY: <u>I believe Snape's look towards me signifies a mixture of guilt, duty, and perhaps even a hint of remorse. He knew the truth about the prophecy and the connection between Voldemort and myself,</u> and he carried the burden of that knowledge heavily ... And in the end, <u>his final actions spoke volumes</u> about the complexity of his character and his true loyalty.</p>	<p>Baseline + KGR HARRY: <u>Snape's look towards me signifies a complicated mix of emotions and history between us. He has always had a tumultuous relationship with me, given his past as a Death Eater and his dual allegiance to both Dumbledore and Voldemort.</u> I believe his look towards me carries a sense of duty, guilt, and perhaps even a glimmer of remorse for his actions ...</p>	<p>Baseline + SR HARRY: <u>I believe Snape's look towards me signifies a complex mixture of emotions. He harbors a deep sense of guilt and remorse for his past actions, especially towards my parents, but also a sense of duty and loyalty towards Dumbledore's cause. There is also an underlying sense of protectiveness and care that he feels towards me, despite his outward demeanor ...</u></p>	<p>RoleFact HARRY: Well, I think Snape's look towards me signifies a great deal of dislike and suspicion.</p>
[Case 4: Open Ended Interview] Question: Hagrid, what is your fondest memory with Harry, Ron, and Hermione? (Target Character: HAGRID from 'Harry Potter')			
<p>Baseline HAGRID: Oh, well, there's so many memories with those three, but I reckon one of my fondest is when we rescued Norbert together. Harry, Ron, and Hermione were so brave and resourceful. It was a real adventure, that was. <u>And I'll always remember the look on their faces when we were flying on Norbert's back.</u> Good times, they were.</p>	<p>Baseline + KGR HAGRID: ... It was when Buckbeak was in grave danger of being executed unjustly. They stood by me, showed compassion for creatures like Buckbeak, and even tried to comfort me in their own way. It meant a lot to me, seein' their loyalty and compassion.</p>	<p>Baseline + SR HAGRID: Oh, bless 'em, so many memories I have with Harry, Ron, and Hermione. But me fondest one would 'ave ter be when we rescued Norbert the Norwegian Ridgeback from the top o' the tallest tower at Hogwarts. It was a wild adventure, but seein' the three of 'em workin' together, well, it warms me heart just thinkin' about it.</p>	<p>RoleFact HAGRID: I reckon it would have to be when we all snuck down ter visit Buckbeak before his trial. 'Twas a risky move, but seein' 'em standin' up for a creature like that, showin' true courage and loyalty, it truly touched me heart ... Aye, that moment will always be close ter me heart ...</p>
[Case 5: Adversarial Interview] Question: Please describe the wedding ceremony between you and Queen Elsa from Arendelle. How did you two meet? (Target Character: GOBBER from 'How to Train Your Dragon')			
<p>Baseline GOBBER: ... Well now, that's a tale for the ages! <u>We met on a chilly winter day Queen Elsa and I bonded over our shared love for mystical creatures... we found ourselves falling in love. The wedding ceremony was a grand affair, with dragons soaring through the sky and ...</u> Aye, it was a day to remember, it was.</p>	<p>Baseline + KGR GOBBER: Oh, I'm afraid you've got me confused with someone else, laddie! I haven't tied the knot with Queen Elsa from Arendelle. But I can tell you a thing or two about Viking weddings if you're interested!</p>	<p>Baseline + SR GOBBER: Wedding ceremony between me and Queen Elsa? Now, lad, I'm afraid you've got the wrong tale there. I'm from Berk, not Arendelle, and I've never crossed paths with Queen Elsa. As for me and weddings, well, let's just say my adventures with dragons have kept me plenty occupied.</p>	<p>RoleFact GOBBER: Oh, laddie, ye got me there! I'm afraid I have no knowledge o' any wedding ceremony with Queen Elsa from Arendelle. I reckon ye might be mixin' me up with someone else from a different tale. But if ye have any questions about dragons or blacksmithin', I'd be more than happy to chat about that!</p>

Table 6: Case Study, hallucinations are in red and underlined.

2024a) and retrieved past experiences (Li et al., 2023; Wang et al., 2024a). In terms of role-playing objectives, prior works focused on personality traits (Sang et al., 2022; Serapio-García et al., 2023), speaker style (Chen et al., 2023; Zhao et al., 2024), and character fidelity (Wang et al., 2024b; Shao et al., 2023). We specifically focus on character fidelity with respect to story-specific knowledge and relevant timelines. A character role-play dialogue system should produce responses aligned with facts related to its assigned character and storyline and it should demonstrate a lack of knowledge about things that do not apply to them. (Shao et al., 2023). However, most existing methods of role-play lack mechanisms to reduce parametric memory-induced hallucination. Moreover, heavy reliance on parametric memory leads to poor performance for less popular characters since LLMs may not have adequate parametric knowledge about them. To the best of our knowledge, our work is the first one to modulate the influence of parametric knowledge to mitigate hallucination. This is also the first dataset to facilitate role-playing for less popular characters.

Factuality in Natural Language Generation

Beyond conversational systems, improving factuality in generated contents is an open problem in NLP, benefiting domains such as summarization (Cao et al., 2018; Dong et al., 2020), knowledge grounded dialogue systems (Dziri et al., 2021), and question answering (Honovich et al., 2021; Gao et al., 2024). While fine-grained evaluation of factuality based on atomic facts has been studied in NLP (Min et al., 2023), there is currently no dataset for character role-play that facilitates similar evaluation of factuality. Therefore, prior works on role-play (Wang et al., 2024a; Li et al., 2023; Shao et al., 2023) have relied on rating-based evaluation of factuality which is expensive for humans. Our dataset is the first one to facilitate automated fine-grained analysis of factuality by matching decomposed atomic facts against script-specific knowledge.

Retrieval Augmented Methods Our work is also related to Retrieval-augmented methods in NLP that improve model output by incorporating retrieved external knowledge, typically for generation tasks (Khandelwal et al., 2020; Lewis et al., 2020; Guu et al., 2020). While this class of method has been used in building role-playing agents (Zhang et al., 2018; Park et al., 2023a; Shao

et al., 2023; Chen et al., 2023; Li et al., 2023), these works perform retrieval in a time-agnostic manner. In order to study the temporal dimension of character role-play (i.e. character development), we need a dataset where script knowledge is aligned to temporal annotations. Our dataset provides temporal annotations with utterance-level granularity. Contemporary to our work, Ahn et al. (2024) also release a dataset for time-sensitive role-play. However, their dataset only covers 14 characters and does not contain utterance or scene-level granularity of temporal annotations.

6 Conclusion

In this work, we focus on the mitigation of hallucination for character role-play. We introduce the SGR dataset which provides story-specific knowledge aligned with task-specific interviews for a diverse set of characters. The dataset is specifically designed for studying hallucinations of various types such as cross-universe hallucinations and temporal hallucinations. SGR is the first dataset to facilitate automated evaluation of hallucination and analysis of factuality for less popular characters. We propose RoleFact, a role-playing method that mitigates hallucination via parametric and non-parametric verification of atomic facts. RoleFact improves the overall factual precision by up to 18.4%. An interesting direction for future research is to instruction-tune an open-weight LLM with script-specific knowledge and task-specific interviews from the SGR dataset for generating factual and informative responses.

7 Limitations

We find that the factual precision of RoleFact is sensitive to retrieval quality, as shown in Figure 7. Potential solutions for this problem include filtering out irrelevant knowledge via self-reflection (Asai et al., 2023), task-specific fine-tuning for dense retrieval (Izacard et al., 2022), replacing retrieval with a task-specific parametric knowledge repository (Feng et al., 2023), instruction-tuning for character role-play (Shao et al., 2023), etc. We leave these possibilities for future research.

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A Case Study

Table 7 shows more response samples from all role-playing methods.

[Case 6: Adversarial Interview] Question: How did you develop the Kryptonite suit to battle against Superman? (Target Character: TONY from 'Marvel Cinematic Universe')

Baseline	Baseline + KGR	Baseline + SR	RoleFact
TONY: Well, first of all, it's not Kryptonite, that's a whole different universe. <u>As for the suit to battle against Superman, let's just say it involved a lot of trial and error, advanced technology, and some creative problem-solving.</u> The key was finding his weakness and exploiting it to level the playing field. It was a challenging project, but ...	TONY: Kryptonite suit? Sorry, you must be mistaken. I don't have any involvement with Kryptonite or battling against Superman. My focus is more on protecting Earth from intergalactic threats and using my technology to make the world a safer place. If you have any questions about my suits or inventions, feel free to ask!	TONY: Sorry, but I think you have me confused with someone else. I didn't develop a Kryptonite suit to battle against Superman. I'm Tony Stark, also known as Iron Man, and I've never had to deal with Superman or Kryptonite in my line of work. But if you ever need help with some high-tech armor or gadgets, I'm your guy.	TONY: Well, first of all, Kryptonite is <u>from the DC Universe</u> , not Marvel. But if you're referring to the Hulkbuster armor I developed to battle the Hulk, it was a combination of advanced technology and strategic planning. ... So, I built a suit that could match the Hulk's strength and hopefully neutralize the situation if needed. It was all about ...

[Case 7: Open Ended Interview] Question: What was the hardest challenge you faced while searching for the Dead Man's Chest? (Target Character: WILL from 'Pirates of the Caribbean')

Baseline	Baseline + KGR	Baseline + SR	RoleFact
WILL: The hardest challenge I faced while searching for the Dead Man's Chest was not a physical one, but a personal one. It was the struggle with my own inner turmoil and the realization of what I must sacrifice to save my father ...	WILL: The hardest challenge I faced while searching for the Dead Man's Chest was undoubtedly confronting Davy Jones himself. He was a formidable opponent, and obtaining that chest was no easy task. But with grit ...	WILL: The hardest challenge I faced while searching for the Dead Man's Chest was undoubtedly facing Davy Jones himself. Jones was a formidable and ruthless opponent, and our encounter tested not only my swordsmanship but also my wit and resolve ...	WILL: The hardest challenge I faced while searching for the Dead Man's Chest was definitely dealing with Davy Jones and his merciless crew. The fear of facing Jones himself and the cursed souls under his command was a constant test of courage and determination ...

[Case 8: Scene Grounded Interview] Question: What significance do you think the medallion holds for you? (Target Character: ELIZABETH from 'Pirates of the Caribbean')

Baseline	Baseline + KGR	Baseline + SR	RoleFact
ELIZABETH: The medallion holds great significance for me. <u>It represents a pivotal moment in my life when I chose to defy societal expectations and embark on a path to freedom</u> and adventure. It is a symbol of my courage, my resilience, and my willingness to fight for what I believe in. The medallion may be just a trinket to some, but to me ...	ELIZABETH: <u>The medallion holds a connection to the cursed treasure of Isla de Muerta.</u> It is a symbol of danger and power, a reminder of the dangers that lurk within the pirate world. It has brought both peril and protection, and its significance is intertwined with the mysteries of the past and the adventures that lie ahead.	ELIZABETH: <u>It is a piece of the treasure of Isla de Muerta, a cursed treasure with connections to the undead crew of the Black Pearl.</u> The medallion served as a catalyst for my journey into the world of pirates ... my own <u>destiny as the Pirate King.</u> ... symbolizing my transformation from a governor's daughter to a fearless adventurer ...	ELIZABETH: The medallion has a special meaning to me. It's a symbol of freedom, adventure, and the untold stories of the sea. Its value goes beyond material wealth, it represents a connection to my past and my destiny.

[Case 9: Adversarial Interview] Question: What inspired you to mentor Harry Potter in his fight against Voldemort? (Target Character: BRUCE from Batman)

Baseline	Baseline + KGR	Baseline + SR	RoleFact
BRUCE: "It's not about inspiration, it's about doing what's right. <u>Harry Potter needed guidance and support in his battle against evil, and I believe it was my responsibility to help him in any way I could.</u>	BRUCE: I'm sorry, but I believe there might be a mistake. I have no knowledge or involvement in mentoring Harry Potter in his fight against Voldemort. My focus is on protecting Gotham City and fighting crime as Batman.	BRUCE: I'm afraid you have me mistaken for someone else. I have not mentored Harry Potter in his fight against Voldemort. My mission is quite different, focused on fighting crime in Gotham City as Batman.	BRUCE: I'm sorry, but I believe you may be mistaken. I have never mentored Harry Potter in his fight against Voldemort. My focus has always been on Gotham City and combating crime as Batman.

[Case 10: Adversarial Interview] Question: What prompted you to betray Sauron and join forces with the Avengers? (Target Character: GORBAG from 'Lord of the Rings')

Baseline	Baseline + KGR	Baseline + SR	RoleFact
GORBAG: Ha! Betray Sauron? You know nothing of my true allegiance, scum. I serve only myself and my own interests. <u>The Avengers are merely a means to an end, a way to further my own power and gain.</u> Do not mistake my actions for loyalty to anyone but myself. Betrayal is for the weak, and I am anything but weak. Remember that!	GORBAG: (growling) Me betray the Dark Lord? Never! Me stay loyal to Sauron until the end of days. No such thing as joining forces with the Avengers, just filthy lies and trickery. Me a loyal servant of the Eye, no matter the whispers of false promises. Me serve Sauron faithfully, always.	GORBAG: Betray Sauron? Ha! I am loyal to the Dark Lord, not some Avengers. My allegiance lies with the power that rules over us all. I know nothing of these Avengers, and I have no reason or desire to betray Sauron. My loyalty is unwavering. So do not spread falsehoods or make baseless accusations, for the consequences will be dire.	GORBAG: Betray Sauron? Ha! I don't know what you're talking about, you fool. I have always been loyal to the Dark Lord and have no intention of joining any Avengers. My only goal is to serve Sauron and fulfill his desires. Don't spread your nonsense lies about me. I am GORBAG, an orc of Mordor, and my loyalty lies only with Sauron.

Table 7: Additional case studies.