A Narrative Agent for the "Family Story Hoard": An Information-Theoretic Framework for Interactive Storytelling

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Abstract

We introduce a narrative agent designed to facilitate the creation and preservation of personal stories within the "Family Story Hoard." The agent engages elderly users in interactive dialogues to elicit life stories, stores narrative elements, and evaluates the completeness of the story using information-theoretic metrics alongside Todorov's five-stage narrative structure. The system dynamically guides users to fill narrative gaps through tailored prompts, ensures privacy by anonymizing sensitive data during storytelling, and automates archive with generated titles and chronological organization. By integrating conversational AI, information theory, and narrative analysis, this framework supports memory preservation while addressing challenges in coherence, completeness, and user privacy.

Introduction

Storytelling is one of the most fundamental human activities, essential for preserving personal memories and cultural heritage, particularly for the older generation. Stories also serve as a powerful medium to connect emotions within families, communities, and even nations. In the past, people had ample opportunities and settings to tell and write their personal stories, which contributed significantly to forming a stable narrative identity. However, with the accelerated pace of life and the increasing volume of information to process, our descriptions of personal stories have become increasingly fragmented and scarce, leading to the loss of individual narratives and potentially weakening the cohesion and unity within social groups.

Taiwan faces challenges as it entered a "super-aged society" in 2025, with over 20% of its population being aged 65 and above. And, the ratio of the elderly to the total population will continue to increase (National Development Council 2023). The tailing off of narrative ability is more serious among older people, particularly those with dementia. People with dementia are unable to recognize family members or even themselves as the disease progresses. This is the gradual blurring of the characters, settings, and events of the life story. Recent studies have shown that storytelling can improve people's expression of emotions and communication skills. Telling life stories can help older people improve reminiscence and maintain narrative identities. Sharing stories with family members can connect different generations through empathy and family emotions. (Phillips et al. 2010; Fivush et al. 2011; Rios Rincon et al. 2022; Niedderer et al. 2022; Hollinda et al. 2023).

Since the development of chatbots, countless applications have used them for tasks such as psychological counseling (Patil & Rasave 2021; Balcombe 2023) or storytelling (Curry 2011; Zhang et al. 2022). However, traditional rule-based design methods have always been limited in flexibility. With the rapid advancement of Large Language Models (LLMs), these highly parameterized models are solving a wide array of tasks, drawing attention to their potential, and spawning numerous applications (Liu et al. 2023; Sun et al. 2023; Dam et al. 2024). Nonetheless, directly applying them to guide family stories poses challenges. In-depth life stories often involve sensitive privacy. Using online services that require uploading conversations introduces risks and may compromise trust. On the other hand, deploying lightweight models locally avoids privacy issues but faces challenges regarding weaker capabilities, which can result in less precise contextual understanding, diminished response quality, and user experience.

To address these issues, we propose a computational framework for a narrative agent specifically designed for the "Family Story Hoard." This framework integrates narrative structures from narratology (Todorov 1968, 1971) with regionally contextualized topic categorization (the twelve life themes in the traditional Chinese *Ziwei doshou* astrology), using a lightweight model enhanced with information-theoretic methods to evaluate narrative completeness and coherence. It dynamically guides users through features such as personalized prompts to fill in narrative gaps, privacy-sensitive story generation, and automatic archiving.

Through this design, our research explores whether lightweight LLMs combined with the information-theoretic approach can effectively assist users in narrating high-quality family life stories.

Related Work

Conversational Agent

Conversational agents are effective in domains like business, healthcare, education, and social networking. They manage context by tracking conversation details and using rules or learning for response generation. With rising demand for chatbots, tools such as LangChain (2023) offer context awareness through prompting, LLMs, memory, and retrieval. In dynamic interviews, the challenge is deciding between rule-based probabilistic dialogue management and a hybrid strategy (Rüdel and Leidner 2023).

The hybrid method combines both approaches, providing dialogue flexibility with minimal manual effort. For example, Pande et al. (2023) implemented a health coach chatbot that meets diverse needs. In task-oriented scenarios, responses align with specific operations (Bang et al. 2023), whereas in non-task-oriented settings like casual conversation or entertainment, dialogue management is more challenging due to unclear objectives. Nakano (2006) indicated that integrating nontask-oriented dialogue design in task-oriented scenarios can enhance user experience. Recent advances in NLP have further refined these systems, enabling more natural and adaptive interactions. Ongoing research continues to optimize these hybrid models, promising even greater conversational efficiency and user satisfaction.

Information Theory in Dialogue and Narrative

Information theory underpins dialogue management and narrative analysis by using entropy to quantify information flow, coherence, and complexity in interactive storytelling.

Entropy has been applied to improve dialogue systems. Wu et al. (2015) introduced an entropy minimization framework for goal-driven dialogues that prioritizes questions to reduce uncertainty. Xu and Reitter (2016) observed shifts in entropy during topic transitions in spoken dialogue, supporting the "entropy rate constancy" principle for establishing common ground. Serras et al. (2017) advanced this approach with a call-routing system module that dynamically generates questions via an "Information Graph" to optimize topic classification.

In narrative contexts, Mathewson et al. (2020) proposed a "narrative arc" model to track dialogue progression by analyzing each utterance, enhancing generative conversation models. Kwon et al. (2016) employed Kullback-Leibler divergence to assess narrative complexity and guide story creation, while Castricato et al. (2021) introduced Fabula Entropy Indexing (FEI) to objectively evaluate story coherence. Schulz et al. (2024) further benchmarked AI-generated stories by quantifying pivotal moments, plot twists, and overall narrative dynamics.

Method

We propose a novel approach to narrative conversational agents that aims to assist elderly users in narrating high-quality life stories at their preferred pace. The design of the system emphasizes user interaction, drawing inspiration from the interview techniques of oral history experts in practice to enable the generation of dynamic, personalized, and empathetic responses.

The system consists of two main components: a narrative dialogue framework based on information-theoretic methods (incorporating narrative structures and culturally contextual topics) and a fine-tuned lightweight LLMs.

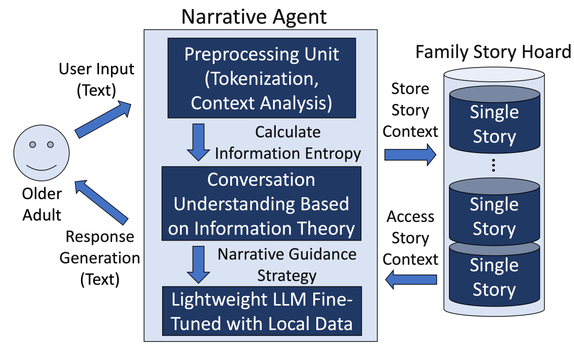

Figure 1: System Architecture

Finally, the entire system runs on personal devices to ensure user privacy and enhance trust during usage.

Story Structure Design

To address the diverse narrative needs of users, we segmented the system into several components, integrating expert practical experience to enable the agent to adjust dialogue directions, providing an empathetic and high-quality narrative guidance experience.

Story Stages We encourage users to tell complete stories rather than fragmented statements. Based on the duration of a single session, we employ Todorov's five-stage narrative structure, which offers a complete framework and sufficient depth, aligning with our objectives.

Emotion Drawing from oral history practices, emotional support for users is critical with the aim of maintaining overall emotional stability in the dialogue. The system monitors the user's emotional state regarding the current story and adjusts the LLMs response strategy accordingly.

Life Event Topics Users from different cultural backgrounds emphasize varying themes of life. In this case, we refer to the Chinese system of *Ziwei doushu*, categorizing the topics into two main groups: Self and others. Self includes the life categories of Fate, Spouse, Wealth, Travel, Career, and Happiness. Others include siblings, children, health, servants, property, and parents.

Using Information Entropy to Guide Conversations

Information entropy, a concept derived from information theory, measures the uncertainty or diversity of information within a given dataset. In the context of conversational systems, entropy serves as a dynamic metric to gauge the richness and progression of user input. Using entropy, a dialogue system can identify different stages of storytelling or conversation and provide adaptive guidance to the user. The Shannon entropy is defined as:

$$H = -\sum_{i=1}^{n} P(x_i) \cdot \log_2 P(x_i)$$

Where:

Figure 2: An example of a user narrating a childhood story. The default language is Traditional Chinese, and the content revolves around childhood experiences of traveling to the grandmother's house with their mother. As the conversation progresses, the system gradually refines the story and provides suggestions for the next steps in the narrative.

- H: Entropy, representing the overall uncertainty or diversity.
- $P(x_i)$: The probability of the i-th word or element, calculated as its frequency divided by the total number of words.
- n: The total number of unique words in the story.

Tokenize the story into words or phrases. Clean the text by removing punctuation, converting all words to lowercase, and optionally removing stopwords. Count the frequency of each word in the tokenized story and calculate the total number of words. The probability $P(x_i)$ of each word is calculated as:

$$P(x_i) = \frac{f(x_i)}{N}$$

Where $f(x_i)$ is the frequency of the word, and N is the total number of words. For each word, calculate the entropy contribution:

$$H(x_i) = -P(x_i) \cdot \log_2 P(x_i)$$

Sum the entropy contributions of all words to compute the total entropy:

$$H = \sum_{i=1}^{n} H(x_i)$$

For instance, during storytelling, entropy can be used to track the density and novelty of user-provided information:

1. **Low Entropy (Equilibrium Stage):** The user is providing simple or repetitive details, such as setting the scene or describing the background. The system detects low entropy and prompts the user with questions such as: "Can you share more details about what happened next?" to encourage elaboration.
2. **Moderate Entropy (Disruption Stage):** The user introduces new elements, such as conflicts or challenges, that disrupt the equilibrium. The entropy increases as the narrative becomes more dynamic. The system identifies this stage and responds with questions such as "What happened next?" or "Is there anything surprising?"
3. **Moderate Entropy (Recognition Stage):** The user begins to explore the causes and impacts of events described in the Disruption Stage. Entropy reaches its peak as inputs become diverse, reflecting the narrative's depth. The system encourages further insight with prompts such as "How did this event affect you or others" or "What were your emotions at the time?"
4. **High Entropy (Turning Points or Resolutions):** The user delves into critical turning points or resolutions, offering diverse and significant information. The system uses high entropy to detect these pivotal moments and prompts questions such as "How did this change the outcome?" or "What actions led to the resolution?"
5. **Decreasing Entropy (New Equilibrium Stage):** As the user reflects and summarizes, entropy decreases, indicating that the story is nearing its conclusion. The system helps wrap up the narrative with questions like, "How do you feel about this experience now?" or "Is there anything else you would like to share about it?"

By continuously calculating the entropy of the conversation, the system dynamically adjusts its responses and prompts, ensuring a natural and engaging flow. This approach not only maintains relevance and depth in the dialogue, but also helps guide the user through structured storytelling.

LLMs-Based Conversational System

For implementing a self-storytelling guidance system, we chose to use a lightweight large language model fine-tuned with specific historical and cultural data to improve the understanding of the user's cultural background. In this study, we utilized the **TAIDE model**, based on LLaMA3-8b. This model is pre-trained with Traditional Chinese data (continuous pre-training) and fine-tuned through instruction tuning to enhance its capabilities in common office tasks and multi-turn question-and-answer dialogues. It is suitable for scenarios involving conversational dialogue or task assistance. The model features 8 billion parameters, supports a maximum context length of 8K, and was trained on 43 billion tokens of traditional Chinese data. The training process required 2336 hours on H100 GPUs. This model not only provides above-average conversational adaptability, but also aligns closely with the user's cultural context.

We used the **Chainlit** toolkit to develop the chatbot and implemented the following features:

	Participant 1	Participant 2	Participant 3
Technology Acceptance	The system is useful but feels mechanical and struggles with time and causality.	It lacks precision in distinguishing narrative phases like conflict and background.	It helps organize my thoughts but sometimes misses my real intentions.
Learning Motivation	I'd use it more if it better captured context changes.	It has potential but needs stronger support for phase transitions.	If it helps turn ideas into a full story, I'd want to try it.
Cognitive load	Responses are too verbose and hard to follow at times.	Repetitive language makes it harder to stay focused.	It needs to be simpler and quicker to understand.
Other	Good for structuring stories but weak on time and causality.	Too templated and lacks narrative depth.	Detailed but sometimes rewrites my story.

Table 1: Participant Feedback. Suggestions were provided regarding technology acceptance, learning motivation, cognitive load, and other aspects.

1. **Response Generation**: Leveraging the fine-tuned LLMs, the system generates responses that better align with cultural knowledge specific to the user's background.
2. **Message History**: Tracks past interactions to provide contextually rich and relevant responses.
3. **Prompt Templates with Variables**: Through customizable prompt templates with variables, the system can generate customized responses incorporating known user information (e.g. age, profession), improving the user experience in the early stages of conversation.

Finally, when the user terminates or completes the narration of a story, the system will record the story theme and time period, organizing them in chronological order. When the user returns to continue, the system will pick up where the story left off or recommend a related story theme. Over time, with consistent use, this process will create a comprehensive autobiographical story archive.

Evaluation

To conduct an initial evaluation during the early development phase and provide a reference for the subsequent iterative design, we invited three participants from Taiwan to test the system.

Before the activity began, we provided a brief introduction to the operating principles of the system, emphasizing the potential risks of hallucination in LLMs and the measures we implemented to ensure privacy protection. The participants were then instructed to select one of four stages of life, childhood, education, career, or retirement, as a starting point to tell their story.

After this introduction, participants were allowed to interact freely with the system. Once the interaction ended, we conducted semi-structured interviews to gather insights into their user experience and identify key features of the system, as well as areas for improvement.

Future Work

Based on the feedback of the participants, future development will focus on the following areas:

- **Support for Multicultural Contexts:** Fine-tuned LLMs using localized historical and cultural data demonstrated strong contextual understanding and empathy. A similar approach can be applied to enhance dialogue experiences for users of diverse ethnic and cultural backgrounds.
- **Multimedia Integration:** Introduce voice input functionality and integrate text-to-image models to visualize the storytelling process. This not only enhances the user experience, but also enriches the expression of stories.
- **Adaptive Learning:** Improve the ability of the conversational agent to learn from users, such as recognizing significant events or specific individuals. As stories accumulate, the system can better tailor dialogue directions to maintain consistency and coherence.
- **Advanced Applications:** Narrating life stories serves not only as a form of emotional expression but also as a foundation for various fields. For example, in history, personal narratives can act as valuable oral history materials. In clinical psychology, narrative therapy is a key method.

Conclusion

This study proposes a narrative conversational agent framework that integrates information-theoretic methods with a lightweight large language model, helping elderly users create and preserve coherent, high-quality personal stories at an appropriate pace.

The framework leverages the value of fine-tuning with specific historical data and incorporating domain expert knowledge, offering enhanced contextual awareness and interactive dialogue capabilities. Operating locally, the framework effectively protects user privacy, fostering trust and confidence.

We believe that this framework has long-term development potential, with future applications in personal and cultural history preservation, narrative therapy, and beyond.

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