Integrating Todorov's Narrative Framework in Dialogue Management of An Oral History Interview Chatbot

Cheng-En Tsai[1,*,†], Fanfan Chen[2,‡] and Jane Yung-jen Hsu[3,§]

[1]National Taiwan University, No. 1, Section 4, Roosevelt Rd, Da'an District, Taipei City, 106, Taiwan(R.O.C)
[2]National Taipei University of Business, No.100,Sec. 1,Fulong Rd.,Pingzhen Dist., Taoyuan City 324,Taiwan(R.O.C)
[3]Chang Gung University, No. 259, Wenhua 1st Rd., Guishan Dist.,Taoyuan City 333,Taiwan(R.O.C)

Abstract

This study proposes a dialogue manager integrating Todorov's narrative scheme to guide oral history interview activities. The framework employs a hybrid dialogue management strategy, incorporating information theory, to cope with different situations, topics, and conversational behaviors, assisting users in conducting interviews with more professional quality. In addition, it utilizes relevant natural language understanding technologies to enhance the user experience of both the interviewer and the interviewee.

Keywords

Dialogue Management, Conversational Agent, Natural Language Processing, Large Language Model, Oral History, Narratology, Todorov

1. Introduction

Focusing on oral history interviews in Taiwan, we have developed an interview guidance chatbot for interviewers without professional training. An expert in narratology participated in the design of the chatbot's dialogue framework. The target users of the interview guidance chatbot are the general public, provided with the basic historical knowledge and the corresponding strategy recommendations needed for conducting interviews. The intended interviewees in this study are older adults or local elders who may not be able to independently recall or articulate effectively due to physical or psychological factors. A qualified interviewer must demonstrate empathy and engage in appropriate pacing and unbiased interaction, guiding the interviewee to make systematic statements.

The interview guidance chatbot involves task objectives (guiding the interviewee to narrate stories) and general conversation (emotional companionship). To address dynamic changes in interviews, the primary objective is to determine when to use rule-based Dialogue Management (DM), probabilistic DM, or a hybrid strategy [1]. Furthermore, the integration of technologies such as emotion recognition to enhance user experience should be carefully calibrated based on feedback from both experts and users.

Therefore, this study bases its approach on the needs of oral history research, combining narrative structure as the foundation for switching DM and the use of technology in the interview guidance chatbot. This integration aims to create a more effective and responsive system that can adapt to the varying demands of oral history interviews. It serves as a supportive tool for both inexperienced interviewers and their subjects. The main contributions of this study are:

- Combining appropriate DM strategies to form a hybrid approach that can adapt to different situations, thereby assisting in the conduct of interviews;
- Integrating narrative structure to provide clear guidelines for the smooth transition of DM strategies;

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* Corresponding author.
† These authors contributed equally.
d11944008@csie.ntu.edu.tw (C. Tsai); ffchen@ntub.edu.tw (F. Chen); yjhsu@cgu.edu.tw (J. Y. Hsu)
https://iagentntu.github.io/people/Cheng-En_Tsai.html (C. Tsai); https://iagentntu.github.io/professor/Jane.html (J. Y. Hsu)
0009-0002-9845-3579 (C. Tsai); 0009-0005-6893-6619 (F. Chen); 0000-0002-2408-4603 (J. Y. Hsu)

- Embedding suitable Natural Language Understanding (NLU) technology components to enhance the user experience for both interviewers and interviewees.

2. Related Work

2.1. Narratology and Oral History

The term "narratology" was coined by Todorov in 1969 to theorize the grammar of narratives modeled on structuralist linguistics [2]. He defined narratology as "the science of narrative," precisely an approach of natural science modeled on Linnaean taxonomy [3]. In fact, the science of narrative existed much earlier than the coinage of the term. Aristotle's *Poetics* [4] is the earliest treatise of narratology. In 1928, Propp's proposed a model to represent Russian folktales as combinations of 31 functions composed of actions and events and seven roles with "spheres of action" [5]. The science of narrative was further developed by French structuralism. In 1955, Lévi-Strauss developed a grammar for mythology, precisely a mathematical formula for narrative mediation and rationalization of universal conceptions of myths [6]. Although the structuralist approaches to narratology suffer criticism for their formalism and reduction, this characteristic makes the mutual illumination between computer science and poetics feasible. It suffices to reference some definitions and keywords of narratology. Structuralists claim their method to be scientific. Ricoeur defined narratology as "the simulation of narrative intelligence" [7] and developed a comprehensive narrative theory of threefold mimesis [8]. Aristotle's *mimesis* implicates probability and imitation, while *muthos* presents a model of the rules of composition [4]. Bal propounded a trio narrative structure with *fabula* as the scheme or model of elements and story as the scheme of event ordering [9]. In interdisciplinary terms, narratology offers different narrative frameworks and aspects for computational narrative understanding and generation, such as Propp's 31-function structure, Campbell' monomyth or Hero's Journey structure [10], Todorov's narrative schematic formulation of equilibrium-disequilibrium, and Genette's narratology of figures and narrative discourse [11][12][13].

Oral history is the collection of historical information or oral reminiscences [14][15], obtained through interviews that preserve a person's life history or eyewitness accounts of a past experience. Whether a life history or eyewitness account, both pertain to narrative interpretation and construction. To narrate is to understand and interpret [16]. Conventional quantitative research approaches involve the process of threefold mimesis: The historian's narrative refiguration (mimesis 3) and figuration (mimesis 2) of documents and information, and the prefiguration stage (mimesis 1). In the wake of the narrative turn in anthropology, rhetoric, literature, psychology, and philosophy, this turn occurred in history, especially with the revival of oral history [17][18][19][20][21]. Grele defined oral history as a "conversational narrative" or "communicative event" that takes place in real time between real people [22][23]. Traditional historians emphasize the "what was said" instead of the "how it was said." The difference between story and narrative lies in "what" and "how." When it comes to "how the story is told," it involves "narrative."

Narrative is ubiquitous in oral history in recent years. Oral history goes in tandem with narrative, as we consider interviewees as narrators, and answers or responses as narratives. Conventional historians regard oral testimony as a source of information or facts on events in history. Portelli foregrounded the significance of the narrative, indicating that the narrative can also be viewed as an event in itself, revealing the narrator's attitude to events, the subjectivity, imagination and desire, embedded in history [24]. Narrative constructs the ontology of personal experiences. The interviewee is a first-person narrator who frames his/her personal account of past events. Each individual narrative communicates with one another and extends to reveal a cultural and communal narrative. Narrative theory or narrative analysis is becoming a mainstream approach, as editing or rewriting oral history interviews is a joint construction of a narrative by the narrator and oral historian [25][26]. The interview initiates the creation of the narrative on the part of the interviewee, but the construction of the narrative continues to be completed by transcribing, editing, and interpreting.

2.2. Dialogue Manager

The dialogue manager can manage context by remembering the course of the conversation and specific messages. It can decide the following response in the dialogue through rules or learning. With the increasing need for chatbots, many software has functionalities like LangChain [27], which achieves context awareness and reasoning through basic prompting and LLMs, memory, and retrieval.

In terms of methods, DM can be categorized into rule-based, data-driven, and hybrid approaches. Whereas rule-based DM requires extensive manual work and can be rigid, data-driven methods need high-quality data. The hybrid method combines both features, maintaining a certain level of dialogue flexibility with minimal manual effort, which can be very effective in specific contexts. For example, Pande et al. [28] employed a hybrid method to implement a health coach chatbot that meets multiple needs.

Regarding objectives, in task-oriented scenarios, responses correspond to specific operations [29]. In contrast, in non-task-oriented scenarios like casual conversation or entertainment, it is more challenging to determine the DM method due to the need for clear goals. M. Nakano [30] indicated that integrating non-task-oriented dialogue design in traditional task-oriented scenarios can enhance user experience.

Recent oral history research started using AI technology to assist in data analysis and narrative construction. Nonetheless, existing studies work more on the post-interview narrative construction by the interviewers or oral historians and guided dialogues that facilitate the interviewee to tell stories. Pandza utilized NLP to process metadata mining and topic mining based on the data obtained through interviews to do narrative analysis [31]. Few studies work on the perspective of the interviewee's narrative utterances. The study of Halperin et al. used conversational storytelling agent prototypes and models to test user experience in storytelling [32]. The finding shows that the agent is better or more welcomed than human oral historians in that the latter pay close attention to the narrators' historical information while ignoring narrative facilitation. Also, the narrators expressed that they favor the automated agent because it could alleviate burden, anxiety, and shame, compared with humans, who care for the narrators' emotions, feelings, and needs in real time.

2.3. Information-Theoretic Dialogue and Narrative

For the dialogue manager to safeguard privacy while being effective in a lightweight large language model, we use information-theoretic evaluation of narrative structure to guide the interview. Information theory provides a mathematical foundation for dialogue management and understanding narrative structures. Studying entropy in dialogue systems and narrative structures provides valuable insights into information flow, coherence, and complexity.

Entropy dynamics have already been used to enhance rule-based dialogue systems for direction and coherence. Wu et al. [33] proposed an entropy minimization framework for goal-driven dialogue systems, where questions are prioritized to reduce uncertainty and streamline information retrieval. Demonstrated in a simulated music retrieval task, this approach efficiently shortened dialogue turns and highlighted its applicability in real-world systems. Xu and Reitter [34] examined entropy dynamics in spoken dialogues, revealing that entropy patterns shift during topic transitions. Their study, grounded in the principle of "entropy rate constancy," highlighted how speakers adjust information flow to build common ground, fostering effective communication. Serras et al. [35] advanced entropy-driven frameworks by introducing an automatic dialogue system module for call-routing services. This system dynamically generates questions based on user input, guided by an "Information Graph" to optimize topic classification. This approach improved classification accuracy and user experience, making it suitable for complex, evolving domains.

Incorporating narrative framework, Mathewson et al. [36] propose the "narrative arc" framework to model dialogue progression by analyzing the information revealed in each utterance. This method balances revealing and concealing information to create engaging, collaborative dialogues. Tested with various universe models, it enhances generative conversation models, improving tasks like next-line prediction and interactive dialogue design. The method enhances generative dialogue models, creating

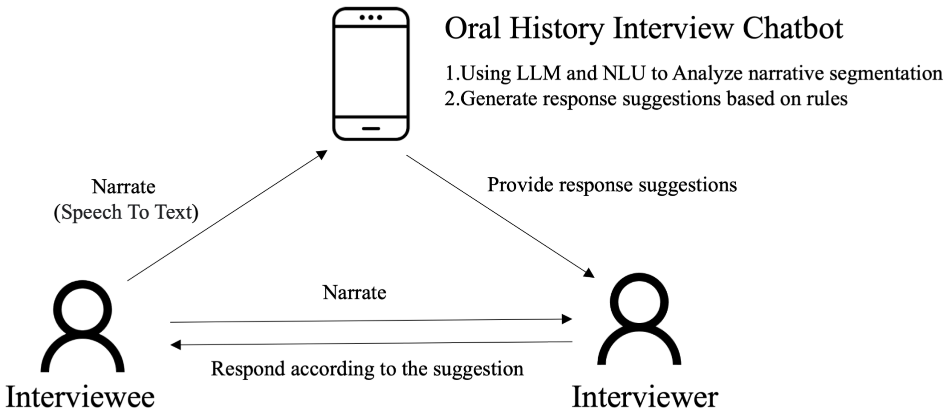

Figure 1: Usage Scenario. Interviewee first describe their own experiences based on the oral history interview questions. The system then analyzes the content and gives the interviewer suggestions for response.

engaging and narrative conversations. Besides, dialogue or narrative generation, information-theoretic models are developed for narrative evaluation. Kwon et al. [37] developed an information-theoretic model to assess narrative complexity, which affects comprehension and engagement. Using Kullback-Leibler divergence, they quantified information flow and proposed methods to guide authors in managing complexity during story creation. Castricato et al. [38] introduced Fabula Entropy Indexing (FEI) for objectively evaluating story coherence. By measuring agreement among readers on true/false questions, FEI distinguished between coherent and inconsistent narratives, proving its utility for evaluating AI-generated stories.

Entropy-based methods have also been applied to literary and poetic analysis. Kozhemyakina et al. [39] investigated Russian poetry using entropy metrics, revealing stylistic features and emotional tones in the works of Pushkin and his contemporaries. This approach highlighted the potential of entropy for examining symbolic and phonetic structures in texts. Zhang et al. [40] analyzed Jane Austen's novels, identifying patterns of information gain that reflect narrative climaxes and plot predictability. Their findings underscored the role of entropy in understanding reader engagement and narrative flow. Schulz et al. [41] extended entropy analysis to benchmark AI-generated stories. Their framework quantified pivotal moments, plot twists, and narrative dynamics, providing a robust tool for evaluating story complexity across genres such as crime thrillers and historical dramas.

The review synthesizes key contributions to analyzing and optimizing storytelling in interactive systems, focusing on how entropy-based frameworks enhance dialogue management, narrative analysis, and story evaluation.

3. Method

This study adopts a user-centered approach to design DM. The process begins by identifying the basic needs of oral history and consulting with a narratology expert to provide a rigorous story structure as a guide for the chatbot. The study utilizes the LangChain [27] open-source framework for the DM aspect, which is employed for modeling dialogues based on rules and frameworks.

For NLU, the study uses the spaCy Toolkit package, allowing for flexible configurations to be implemented.

The interview guidance chatbot is designed to interact with users through the Chainlit, a popular communication application in Taiwan. This choice ensures accessibility and ease of use for the target audience in Taiwan, facilitating the efficient and user-friendly operation of the chatbot to conduct oral history interviews.

In the first iteration, all dialogues were designed using a rule-based approach, following a rigorous process. This approach ensured a structured and predictable interaction, aligning closely with the

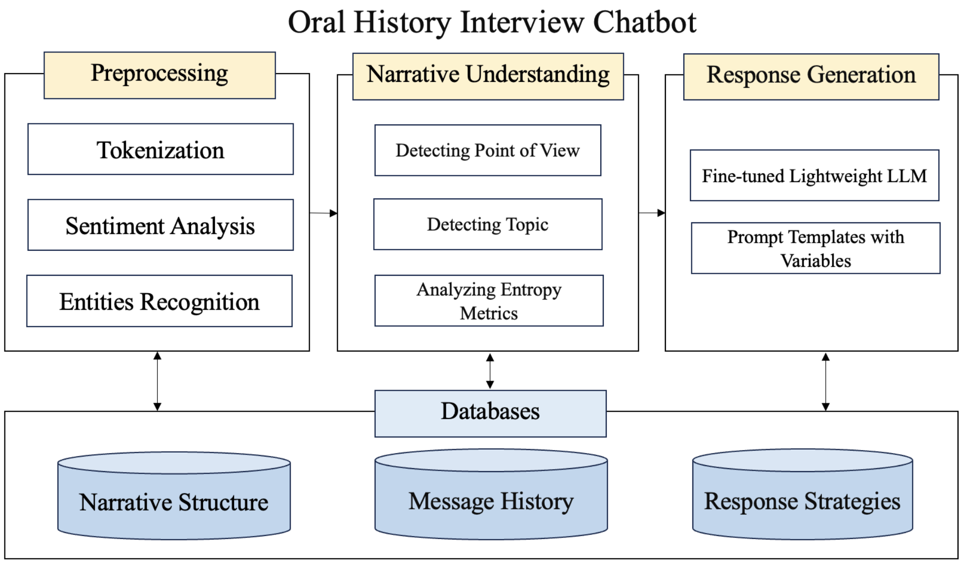

Figure 2: System structure. After the preprocessing and narrative understanding on the dialogue content, responses are generated using a large language model.

predefined narrative framework.

The second iteration implemented a framework-based DM by recognizing named entities (populated from the user's speech). This development marked a shift towards a more dynamic interaction, allowing the system to adapt the conversation based on specific entities mentioned by the user. NLU components were added to identify time, intent, and emotions. This enhancement increased the dialogue's flow and flexibility, enabling the system to respond more accurately to the nuances of the conversation.

The next iteration will focus on integrating large language models (LLMs) to conduct advanced classification and tracking of historical themes and narrative stages based on the interviewee's input. This step aims to use sophisticated AI techniques to provide more relevant and context-aware interview guidance, further enhancing the chatbot's effectiveness in facilitating oral history interviews.

3.1. Conversation Design and Dialog Management

This section will elucidate how the oral history interview requirements and the narrative structure influence the design of the dialogue and the DM strategies.

3.1.1. Interview Needs

From the oral history perspective, ensuring that the dialogue faithfully represents the experiences and observations of the interviewee requires a delicate balance. The interviewer is expected to maintain an impartial stance, avoiding overly subjective questioning; yet, at the same time, they must display sufficient empathy to support the interviewee in recalling and elaborating on past events. Balancing these aspects is challenging and contributes to the difficulty in developing interviewing expertise. To address this, based on the practical experience of oral history experts and the challenges beginners face, we have identified three critical areas of assistance.

1. Provision of historical background knowledge
2. Response strategies
3. General functionalities

Considering the goal of popularizing oral history, we have identified our users as inexperienced members of the general public who may need to become more familiar with historical contexts and lack the time and experience to gather relevant information. This could result in interviewers needing to fully understand or empathize with the content effectively. To address this issue, we use the TAIDE language model [42] to identify the historical era of the interview content and generate the corresponding background knowledge. It can increase the confidence of the interviewer and help with preliminary fact checking after the interview.

Through appropriate responses and interactions, establishing trust with the interviewee within the time allocated to encourage them to elaborate on their memories is critical to a successful interview. Based on practical experience, interviewers need to express emotional support during the process while refraining from expressing too many opinions to avoid leading the interviewee. For this, we have categorized response strategies into four types:

1. Emotional support
2. Probing into details
3. Off-topic reminders
4. Topic transition

The chatbot will track the narrative stages through LLM, understand the psychological states using NLU components, and then decide the type of response based on rules.

General functionalities include the interviewer's self-introduction, an overview of the interview outline, reminders of time, a date schedule, and other content related to the preparatory work. Interviewers can pre-enter defined content and quickly access these general functions through a menu call.

3.1.2. Todorov's Narrative Framework

Todorov's narratology provides a framework for analyzing narratives by examining their fundamental layers and principles. At its base, narratives feature three types of relation: temporal (succession), causal (cause effect), and spatial (parallelism, such as repetition, antithesis, and gradation) [43]. These basic propositions form two core principles of all narratives: succession and transformation. Succession is defined by the propositions of temporal relations. Transformation involves causal and spatial relations. Based on the proportion of these principles, narratives are categorized into mythological (focused on succession with limited transformation), gnoseological (knowledge or perception revelation), and ideological (rule-based behavior) [44].

At the highest level of narrative, a minimal plot progresses from one equilibrium to another or from disequilibrium to equilibrium or another disequilibrium, with episodes either describing states (equilibrium or disequilibrium) or the transitions between them. Todorov's narrative schematic formulation is reduced to two core principles of succession and transformation, underlying two core episodes of states and transitions. An ideal story unfolds in five stages: It begins with a stable situation (Equilibrium) that some force comes to disturb (Disturbance). This results in a state of disequilibrium (Disequilibrium). By the action of a force directed in the opposite direction (Counteraction or Resolution), the equilibrium is reestablished; the second equilibrium is similar to the first, but the two are never identical (New Equilibrium). [3]

3.2. Narrative-Driven Conversation

We begin with a chat to ease the interviewee's tension. The chatbot will show interest in the responses. It avoids interrupting the interviewee's conversation unless it is off topic or emotionally charged. The chatbot continues with sentiment analysis to identify possible narrative disequilibrium during the interview. The unfolding of the story is ruled by the aforementioned Todorovian equilibrium/disequilibrium schematic formulation of five-stage emplotment. The chatbot attempts to help the interviewee open up a narrative space [45]. It detects narrative time during each narrative stage to guide the interviewee into narrative expansion in terms of characters and spheres of actions. If silence occurs, the chatbot would generate relevant information about people, time, and space. It can also invite the interviewee to provide relevant documents, artifacts, or photographs to narrate related events or relations. It pays attention to the interviewee's language and emotional responses; if necessary, the chatbot would suggest to pause the conversation.

3.2.1. Help the interviewee open up narrative space based on the narrative structure

1. **Detecting POV:** The first-person narration, then verify if the interviewee is the hero or the witness of past events? If hero: Follow-up questions on the unfolding of the hero's journey. If witness: Follow-up questions on other characters and time/space setting guiding questions based on turning point events in life: marriage, career, school, travel, etc.
2. **Detecting disequilibrium:** Using sentiment analysis to recognize emotional change. Once disequilibrium detected, follow-up questions on the causes of conflict: you vs. other characters, or you vs. society, or you vs. nature? Follow-up questions on actions: important event in life or ask if the interviewee's choice changed his/her life? Bad Decisions, Educational Achievement, Losing a loved one, Moving, Immigration, War, Injury, Illness, Political events, etc.
3. **Detecting the possible stage of the narrative structure:** Prompt with narrative time: we design topic chronologically to help the interviewee remember past events:
   - Childhood: Birth, family, background, era, best playmates, toys and games played, aspirations as a child, etc.
   - Student: Best classmates, good or bad relationships with classmates, favorite/hated teachers, memorable events, favorite subjects, etc.
   - Career: Colleague relationship, employer, workplace environment, success, difficulties, etc.
   - Marriage & Family: Spouse, romance, children, etc. Friendship: partners, friends, social relationship, etc.
   - Single: Loneliness, activities, social life, friends, family relationships
   - Retired: Loneliness, activities, social life, health, etc.
4. **Detecting deviation from the narrative topic:** The chatbot would help stick with the narrative structure and narrative elements.

Due to the complexity of narrative structures and rhetoric, it is challenging to establish universal rules for narrative understanding; nonetheless, large language models can achieve narrative understanding at the level of recognizing narrative stages.

3.2.2. Using Information Entropy to Guide Conversations

We measure the transitions between narrative stages by calculating changes in information entropy. 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:

- 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):** 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):** The user introduces new elements, such as conflicts or challenges, which 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 (Disequilibrium or Recognition):** The user begins to explore the causes and consequences of disequilibrium and impacts of events. 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 (Counteraction or Resolution):** The user delves into critical counteraction 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):** As the user reflects and summarizes, entropy decreases, indicating that the story is approaching its denouement. 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.

3.3. LLMs-Based Conversational System

For implementing an oral history interview chatbot, We used the **Chainlit** toolkit to develop the chatbot and implemented the following features:

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 variable-based prompt templates, the system can determine the current narrative stage of the dialogue based on calculated information entropy. The identified narrative stage is then added to the prompt variables to generate responses that guide the interview effectively.

Regarding LLMs chosen to generate responses, we opted for a lightweight 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.

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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.

4. Evaluation

This study aims to serve as an auxiliary tool for the general public in conducting oral history interviews, providing essential historical context knowledge, response suggestions, and available functionalities. Based on this, the study seeks to increase the popularity of interview activities and ensure the quality of the interview content.

In the future, the study will use feedback from oral history experts as a basis for iterations and improvements. Additionally, surveys will be arranged for both interviewees and interviewers, covering aspects such as technology acceptance and cognitive load to gauge the specific effectiveness of the chatbot.

5. Future Work

- **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.
- **Adaptive Learning:** The ability of the dialogue manager can be improved to learn from users, such as recognizing significant events or specific individuals. As narratives accumulate, the system can better tailor dialogue directions to maintain consistency and coherence.
- **Advanced Applications:** Personal narratives act as valuable materials in oral history. Narrating life stories serves not only as a form of emotional expression but also as a foundation for various fields. For example, in clinical psychology, narrative therapy is a key method.
- **Refined Computational Models of Narrative:** The five-stage narrative framework using information-theoretic evaluation presents a basic model for guiding narrative interaction and generation. Future work on narrative modeling can include refined detection and generation of propositions of succession and transformation pivoting on temporal, causal, and spatial relations.

6. Conclusion

In this study, a dialog manager integrating narrative structure is proposed. The process begins with identifying the needs of oral history and the framework of narratology. Following this, a rule-based dialogue design is established.

The framework leverages the fine-tuning of specific historical datasets and integrates domain expert knowledge, offering enhanced contextual awareness and interactive dialogue capabilities. The application of information theory provides robust story comprehension and guidance for subsequent interview dialogue suggestions. Operating locally, this framework effectively safeguards user privacy, fostering trust and confidence.

Finally, by incorporating LLMs, the system achieves the tracking of dialogue on historical themes and narrative stages, thereby realizing guidance standards based on the story structure. Continuous improvements will be made in the future based on feedback from historians and interviewers.

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Declaration on Generative AI

During the preparation of this work, the authors used GPT-4o and Grammarly for correction and proofreading. After using these tools, the author reviewed and edited the content as needed and take full responsibility for the publication's content.

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