MovieChat: From Dense Token to Sparse Memory for Long Video Understanding

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https://rese1f.github.io/MovieChat

Abstract

Recently, integrating video foundation models and large language models to build a video understanding system overcoming the limitations of specific pre-defined vision tasks. Yet, existing systems can only handle videos with very few frames. For long videos, the computation complexity, memory cost, and long-term temporal connection are the remaining challenges. Inspired by Atkinson-Shiffrin memory model, we develop an memory mechanism including a rapidly updated short-term memory and a compact thus sustained long-term memory. We employ tokens in Transformers as the carriers of memory. MovieChat achieves state-of-the-art performace in long video understanding.

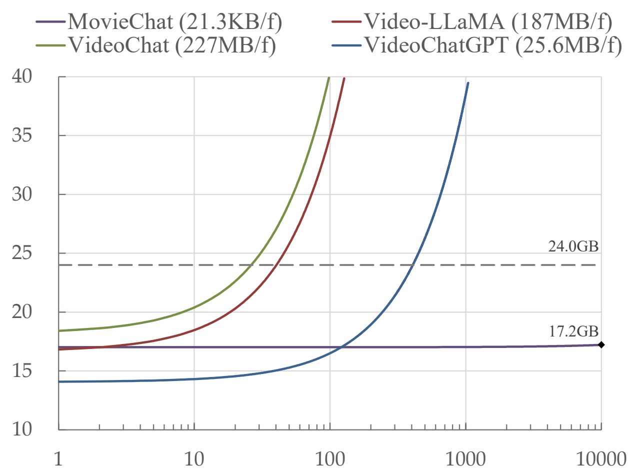


Figure 1. GPU memory cost under gigabyte (GB) (y-axis) v.s. frame number (x-axis) comparison. We test the visual-only inference of all methods at a resolution of 224×224 without frame sampling. While the previous method can only support around 100 frames of inference, **MovieChat** can handle videos with >10K frames on a 24GB graphics card. MovieChat has a $10000\times$ advantage over other methods in terms of the average increase in GPU memory cost per frame (21.3KB to $\sim$ 200MB per frame).

1. Introduction

Recent advances in Large Language Models (LLMs) [11, 17, 60, 78, 82] acheive great success in Natural Language Processing (NLP) field. It is a natural progression to introduce multi-modality [13] into LLMs and turn it into Multi-modal Large Language Models (MLLMs) [1, 18, 24, 27, 29, 40, 41, 43, 50, 53, 55, 76, 88, 100, 101, 110], which is able to conduct multimodal perception and understanding. MLLMs have shown incredible emergent capabilities in various multimodal tasks such as perception (*e.g.*, existence, count, position, OCR), commonsense reasoning, and code reasoning, leading a potential path to Artificial General Intelligence (AGI). Compared to LLMs and other task-specific models, MLLMs provide a more human-like perception of the world, a user-friendly interface for interaction, and a broader range of task-solving capabilities.

Existing vision-centric MLLMs follows the paradigm that utilizing pre-trained LLMs and visual encoder with additional learnable modules (Q-former [18, 41, 43, 106] or simple projection layer [21,50,55,76]). In video field, some previous works [55,106] follow this paradigm to build video MLLMs, while another paradigm [44,85] is that combining existing visual perception tools (*e.g.*, tracking and classification) and LLMs through API to build a system without training. Yet, previously, there was no exploration of a model or system based on long videos (over one minute), and there was also a lack of a standardized benchmark to evaluate the capabilities of these systems in this regard.

In this paper, we present MovieChat, a novel framework that integrating vision models and LLMs to conduct long video understanding tasks. We claim that the computation complexity, memory cost, and long-term temporal connection are the remaining challenges for long video understanding. To this end, we propose a memory mechanism inspired by Atkinson-Shiffrin memory model [4], which including a rapidly updated short-term memory and a compact thus sustained long-term memory.

The contributions of this work are summarized as:

- We present MovieChat, a novel framework that integrating vision models and LLMs, is the first to support long video understanding tasks.
- We propose a kind of memory mechanism to reduce the computation complexity and memory cost, while enhancing the long-term temporal connection.
- We conduct extensive quantitative evaluation and case studies to evaluate the performance of both understanding capability and inference cost.

2. Related Works

2.1. Video Foundation Models

Video foundation models have various applications on downstream tasks (*e.g.*, video question answering [37, 38], video captioning [34, 98], and human action recognition [36, 62, 63]). The common paradigm in the field of video foundation models is now characterized by the combination of extensive large-scale video-language pretraining, followed by fine-tuning on specific downstream tasks [45,46,48,57,77,89,96,111]. Such paradigm depends on end-to-end video-language joint training with pretext pre-training tasks such as masked language modeling [47], masked video modeling [80, 87], video-language masked modeling [25], video-text matching [86], and video-text contrastive learning [96]. These prior arts yield impressive performance in multimodal video tasks. Yet, they can only train with limited video-language pairs or videos without detailed annotations, which leads to difficulties in language-related tasks. With connecting to LLMs, video foundation models serve as visual encoder and achieve state-of-the-art performance in various tasks and become user-friendly.

2.2. Multi-modal Large Language Models

LLMs [11, 17, 60, 78, 82, 83] achieves great success recently. Many works try to build MLLMs [1, 18, 24, 27, 29, 40,41,43,50,53,55,76,88,100,101,110] by combining models of other modalities. Flamingo [1] bridge powerful pretrained vision-only and language-only models and achieve state-of-the-art performance with few-shot learning, simply by prompting the model with task-specific examples. BLIP-2 [41] proposes a generic and efficient pre-training strategy that bootstraps vision-language pre-training from off-the-shelf frozen pre-trained image encoders and frozen large language models. MiniGPT-4 [110] aligns a frozen visual encoder with a frozen LLM, Vicuna [17], using just one projection layer. Otter [40] is trained on MIMIC-IT [39] and showcasing improved instruction-following ability and in-context learning. In video field, ChatVideo [85] treats tracklets as the basic video unit and allow user interacting with the LLMs. VideoChat [44] integrates video foundation models and LLMs via a learnable neural interface, excelling in spatiotemporal reasoning, event localization, and causal relationship inference. VideoChat Longvideo [61] further incorporates LangChain [33] into VideoChat to support video which more than one minutes. Video-LLaMA [106] further leverage pre-trained models ImageBind [28] and LLaMA [82] bootstraping cross-modal training in video following BLIP-2. Yet, those methods fails in handling long video understanding since high computation complexity, large memory cost, and weak long-term temporal connection. Therefore, our main efforts is to introduce memory mechanism to enhance those aspects.

2.3. Long Video Understanding

Understanding long videos is a challenging task in computer vision. Prior arts use 3D volumn [90], object/human-centric [67, 91], or other forms [71, 92] as video representations. There are also several datasets of video-caption/description pairs among various domains such as cooking (*e.g.*, YouCook [19, 108], MPII Cooking [68–70], and TACoS [64, 65]), instruction (*e.g.*, HowTo100M [58] and HiREST [104]), and movie (*e.g.*, MovieQA [79], M-VAD [81], MPII-MD [66], and MovieNet [32]) from different sources such as YouTube [14, 58, 105], Twitter [5–8], Flirck [5, 6], and internet [9]. Yet, those datasets lack diverse and fine-grained dense captioning for long videos.

2.4. Memory Models in Vision Tasks

There are some prior works exploring memory models [74] in various vision tasks in video, such as video object segmentation (VOS) [15, 16, 31, 52, 56, 59, 72, 73, 93, 102], multi-object tracking (MOT) [2,12,22,30,94] and visual object tracking (VOT) [26,49,54,99,109]. MeMOT [12] build a large spatiotemporal memory that stores the past observations of the tracked objects. XMem [15] develop an architecture that incorporates multiple independent yet deeply-connected feature memory stores to handle long videos with thousands frames. We drew the experience of those prior arts and further adopt memory model combining with LLMs. Unlike using embedded feature given by certain visual encoder, we found that using tokens in Transformers [84] as the carriers of memory suitable for both LLMs

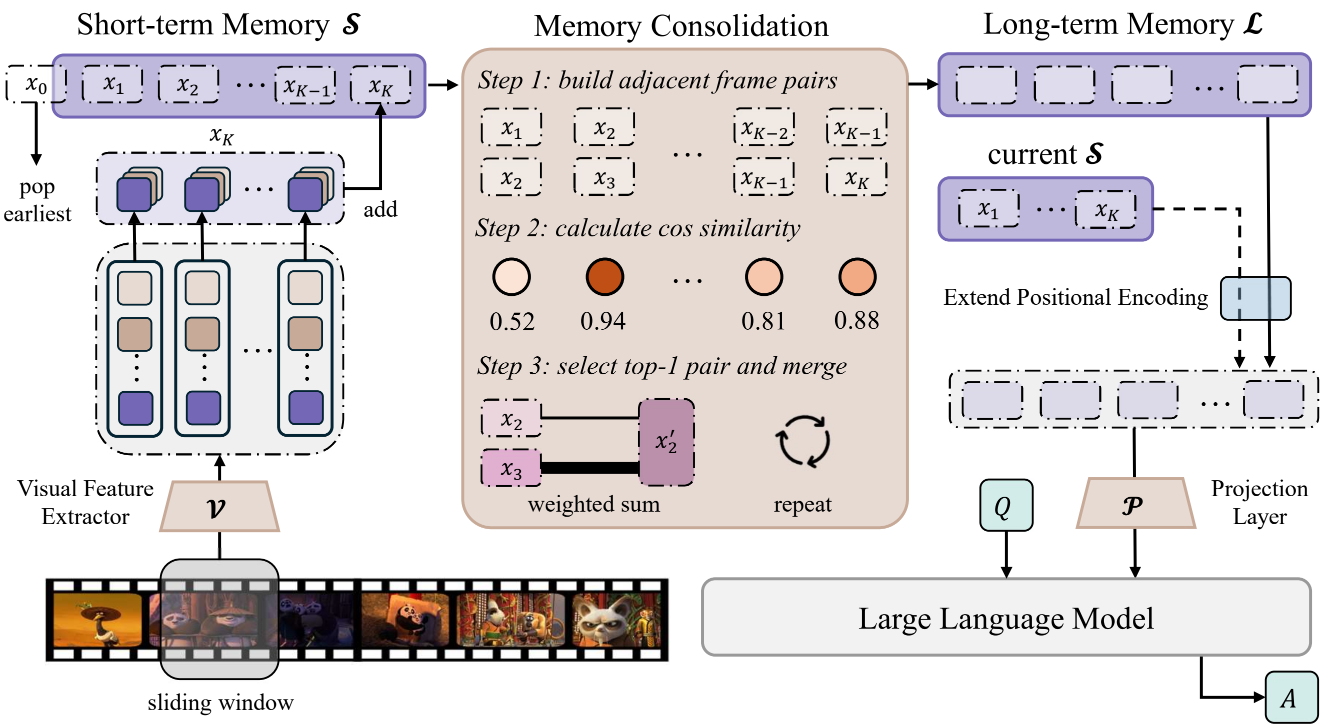


Figure 2. **Illustration of MovieChat.** We use a sliding window approach to extract video features and represent them in token form, which are then sequentially fed into the short-term memory frame by frame. The short-term memory has a fixed length, and when it reaches its set limit, the earliest tokens are popped and consolidated into the long-term memory. We have designed two inference modes: global mode, which exclusively utilizes the long-term memory, and breakpoint mode, which additionally incorporates the current short-term memory as part of the video representation. Breakpoint mode allows for understanding the video at a specific moment in time. Finally, after passing through a projection layer, the video representation is inputted into a large language model for interaction with the user.

and ViT [20] based visual encoder. Our proposed method mainly focus on reducing the redundant of visual tokens in video and building a memory mechanism to pass the information among large temporal range.

3. MovieChat

3.1. Overview

Our proposed method, MovieChat, comprises several key components, including the frame-wise visual feature extractor, the short-term and long-term memory buffers, the video projection layer, and the Large Language Model (LLM), as illustrated in Figure 2. MovieChat is designed for ultra-long videos (>10K frames) understanding through interactive dialogue with the user. To address the impractical storage demands of concurrently storing a vast number of frames in both GPU memory and RAM, we employ a sliding window approach to efficiently process the video. MovieChat supports two inference modes: Breakpoint mode is used to understand a specific moment in the video, providing insights and answers based on that particular frame or scene; Global mode, on the other hand, is employed to comprehend the entire video as a whole, enabling a comprehensive understanding of the overall content and context.

3.2. Visual Feature Extraction

For visual feature extraction, instead of utilizing video-based foundational models such as ViViT [3] or Video-Swin [51], we simply use image-based model to get frame-wise feature in the form of tokens. To be specific, we utilize pre-trained models as our visual feature extractor, including the ViT-G/14 from EVA-CLIP [23] and the Q-former from BLIP-2 [42]. This is mainly because 1) there is no video foundation model makes good alignment with text, and 2) our proposed memory mechanism can effectively capture temporal features. Given input video $\mathbf{v} \in \mathbb{Z}^{T\times 3\times H\times W}$, a sequence of T RGB frames, with height and width H and W, the visual feature extraction by sliding window approach could be formulated as

$$\mathbf{x}_i = \mathcal{V}(\mathbf{v}_i), \mathbf{v}_i \in \mathbb{Z}^{C\times 3\times H\times W}, i = 0, 1, ..., \lceil \frac{C}{T} \rceil, \quad (1)$$

where $\mathcal{V}(\cdot)$ is the visual feature extractor, $\mathbf{v}_i$ are the RGB values of the video clip, $\mathbf{x}_i \in \mathbb{R}^{C\times N\times D}$ are the visual to-

Algorithm 1 Memory consolidation

Require: $\mathcal{S}$ ▷ short-term memory
while $len(\mathcal{S}) > N$ **do** ▷ iterative merge
  for $\mathbf{x}_i$ in $\mathcal{S}$ **do**
    $s \leftarrow sim(\mathbf{x}_i, \mathbf{x}_{i+1})$ ▷ tokens similarity
  end for
  $m \leftarrow max(s)$ ▷ the maximum value index
  $\mathbf{x}_m \leftarrow merge(\mathbf{x}_m, \mathbf{x}_{m+1})$ ▷ merge
  del $\mathbf{x}_{m+1}$
end while

kens, N is the number of tokens, and D is the feature dimension.

3.3. Short-term Memory

Short-term memory stores the visual tokens in a temporary buffer. The previously extracted visual features by sliding window K times without further processing are used to construct short-term memory, which can be formulated by:

$$\mathcal{S} = \{\mathbf{x}_i \mid \forall i = 1, 2, ..., K\}, \tag{2}$$

where $\mathcal{S}$ is short-term memory. Note that we set short-term memory to a fixed length since the role of short-term memory is to assist in understanding based on previous short-term contextual information. The update strategy for short-term memory is similar to the First-in-First-out (FIFO) queue. When a new batch of visual tokens enter, we drop the earliest one that was present. The dropped tokens are further consolidated into long-term memory.

3.4. Long-term Memory

Long-term memory can effectively avoid the problem of catastrophic knowledge forgetting, which is crucial for processing long videos. The features stored in short-term memory are dense tokens, but due to GPU memory and computation cost limitations, directly storing all the tokens dropped from short-term memory into long-term memory buffer in sequence is unavailable. Besides, temporally adjacent frames may exhibit significant similarity in the video. To this end, we propose a method to merge temporally adjacent similar frames. This method transforms the dense tokens to the sparse memory and storing them in long-term memory.

To be specific, as shown in Algorithm 1, we conduct memory consolidation by merging the most similar tokens in the adjacent frames following ToMe [10]. We found that the token enbedding in transformers already summarize the information of each frame for use in cos similarity s as:

$$s = \frac{1}{N}\sum_{j=1}^{N}\left[\cos(\mathrm{x}_i^j, \mathrm{x}_{i+1}^j)\right]. \tag{3}$$

We iteratively conduct this operation until the token count reaches the value set for each consolidation operation.

Extend positional encoding. For long-term memory, the number of tokens exceeds the maximum length of the pretrained model positional encoding. Our model utilizes the positional encoding mechanism following BERT [35], which results in a portion exceeding the length threshold n without available positional encoding. In order to handle long enough long memory, we adopted the hierarchical decomposed positional encoding method proposed by Su *et al*. [75], extending the absolute positional encoding of length n to n^2.

3.5. Inference

Previous methods always use the representation of the whole video to conduct understanding and understanding and question-answering, which may fail in localizing specific moment especially in long videos. To this end, we propose two inference modes for long video understanding task as follows.

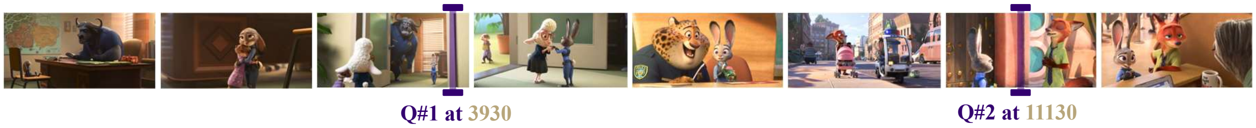
Global mode. Global mode is defined as the understanding and question-answering for the **whole** video. In this case, we only use long-term memory $\mathcal{L}$ as the video representation $\mathbf{V}$.

Breakpoint mode. Breakpoint mode is defined as understanding specific moments in a video. Since events have continuity, we need to consider not only the information directly related to the moments stored in short-term memory $\mathcal{S}$ but also the information indirectly related stored in long-term memory $\mathcal{L}$. Based on this, we hypothesize that when querying the movie at a specific moment, the video representation $\mathbf{V}$ should be the aggregation of $\mathcal{L}$, $\mathcal{S}$, and the current video clip feature $\mathbf{x}$. We found that simply concatenating these items yields excellent performance. We leave further exploration of additional aggregation choices for future work. future work.

After that, the video representation $\mathbf{V}$ goes through a q-former and a linear projection layer before being fed into the LLM, which can be formulated as:

$$\mathbf{A} = \mathcal{L}(\mathbf{Q}, \mathcal{P}(\mathbf{V})), \tag{4}$$

where $\mathcal{P}$ is the projection from visual space to text space, $\mathcal{L}$ is the large language model, $\mathbf{A}, \mathbf{Q}$ are the answer or instruction and the question.



Question #1 **What is Chief Bogo doing?**

Answer #1 In the video, the character Chief Bogo is seen talking to someone on a laptop while sitting at a table in a dark room. Chief Bogo is a cartoon character wearing a brown outfit.

Question #2 **Who is this rabbit named Judy talking to?**

Answer #2 In the video, the rabbit police named Judy is talking to the person in a movie theater, who is a fox.

Question #3 **Can you describe this video?**

Answer #3 The video shows various scenes of an animation with different animals in a restaurant or office environment. At the beginning, we see an animated cartoon rabbit and a deer talking to each other in a restaurant. Next, there is a cartoon bunny talking to a cat at a desk, followed by a scene of a cartoon deer and a mouse talking to each other. The video then continues with the animated cartoon dog and cat sitting at a table in a restaurant, and another scene where a man and a dog are in a room with a computer on a table. There are more scenes of the same characters later on, including one with a bunny and a fox sitting at a desk, and another with a bunny and a dog talking to each other in the background. Finally, there are several more scenes with different animals, including a fox, a mouse, and a cat, all of which are in a different environment.

Figure 3. Question and answer about clips from *Zootopia*, a cartoon, which tells the story of a determined police officer rabbit named Judy who pairs up with a cunning fox to uncover a conspiracy about missing animals and develop an unexpected friendship.

Question #1 **What is she doing?**

Answer #1 In the given video, we see a young woman walking down a street in the city, and a young man also walks down the street behind her. The woman is wearing a red and black outfit.

Question #2 **Where is this couple?**

Answer #2 This couple is standing in the middle of a city street with a black hat on the man's. The scene is shot in a park, and there are a few trees and bushes visible.

Question #3 **Can you tell me what happened in this movie?**

Answer #3 Certainly! In the video, you can see a group of people standing in a park with a green hill in the background. There are also people walking on the street and in a courtyard with trees. Some of the people are holding red umbrellas, and there is a woman wearing a red coat. She is then seen walking down a street at night with a man following her. Next, we see a couple standing on a balcony overlooking a street in the evening with a man walking by and then walking down the street. Towards the end of the video, a group of people are seen walking through a snowy town.

Figure 4. Question and answer about clips from *Goblin*, which tells the story of Kim Shin, an immortal "goblin" who needs to find a human bride to end his endless life but instead meets Ji Eun-tak, a girl fated to die who claims to be the "goblin's bride," leading to a romantic tale unfolding between them.

Method	MSVD-QA		MSRVTT-QA		ActivityNet-QA	
	Accuracy	Score	Accuracy	Score	Accuracy	Score
FrozenBiLM [97]	32.2	–	16.8	–	24.7	–
Video Chat [44]	56.3	2.8	45.0	2.5	26.5	2.2
LLaMA Adapter [107]	54.9	3.1	43.8	2.7	34.2	2.7
Video LLaMA [106]	51.6	2.5	29.6	1.8	12.4	1.1
Video-ChatGPT [55]	**64.9**	**3.3**	49.3	2.8	35.2	2.7
MovieChat *(Ours)*	61.0	2.9	**49.7**	**2.8**	**51.5**	**3.1**

Table 1. Quantitative evaluation on short video question answering. MovieChat achieves competitive results.

4. Experiments

4.1. Quantitative Evaluation

Short video question answering. We conducted a comprehensive quantitative evaluation in this section. We use several widely used open-ended datasets: MSVD-QA [95], MSRVTT-QA [95], and ActivityNet-QA [103] for short video question answering task. The evaluation process is under the assistant of LLM (details in Appendix A) under default hyper-parameter settings as shown in Appendix B. The accuracy and relative score on a scale of 0 to 5 are reported. Compared to previous method [44, 55, 97], MovieChat achieves competitive result although there is no specific design for short video understanding.

4.2. Case Study

We perform an extensive case study of MovieChat on a variety of open-ended long video (such as cartoon movie in and TV series) for long video question-answering and captioning task, including the **global mode** and the **breakpoint mode** as shown in Figure 4. For Q#1 and Q#2, we annotate timestamps in frames. For long videos over 10K frames, MovieChat is still capable of providing excellent responses to questions regarding both the current moment and the entire video content.

5. Conclusion

In conclusion, this paper presents an innovative video understanding system that integrates video foundation models and large language models. By incorporating a memory mechanism inspired by the Atkinson-Shiffrin model, consisting of short-term and long-term memory represented by tokens in Transformers, the system overcomes challenges associated with analyzing long videos. The proposed system, named MovieChat, achieves state-of-the-art performance in long video understanding, surpassing existing systems limited to handling videos with few frames. This approach reduces computation complexity, memory cost, and addresses long-term temporal connections.

The study emphasizes the significance of memory mechanisms in video understanding, enabling the model to retain and retrieve relevant information over extended durations. MovieChat's success has practical implications in domains like video surveillance, content analysis, and video recommendation systems. Future research can explore further improvements to the memory mechanism and the integration of other modalities, such as audio, to enhance video understanding capabilities. This work opens up opportunities for applications requiring a comprehensive understanding of visual information.

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Appendix

A. LLM-Assisted Evaluation

Following [55], we use LLM-Assisted Evaluation for short video question answering task in Section 4.1. Given the question, correct answer, and predicted answer by model, ChatGPT should return the *True* or *False* judgement and relative score (0 to 5). The whole prompt is shown in Figure A1. It takes about 250 tokens per question. We report the baseline results of short video question answering from `https://github.com/mbzuai-oryx/Video-ChatGPT`.

B. Hyper-parameter Setting

Description	Default Value
size of sliding window	10 frames
size of short memory	8 frames $\times$ 32 tokens per frames
size of consolidated memory	64 tokens

Table 2. Hyper-parameter settings of MovieChat.

```
openai.ChatCompletion.create(
  model="gpt-3.5-turbo",
  messages=[
    {
      "role": "system",
      "content":
        "You are an intelligent chatbot designed for evaluating the correctness of generative outputs
        for question-answer pairs. "
        "Your task is to compare the predicted answer with the correct answer and determine if they
        match meaningfully. Here's how you can accomplish the task:"
        "------"
        "##INSTRUCTIONS: "
        "- Focus on the meaningful match between the predicted answer and the correct answer.\n"
        "- Consider synonyms or paraphrases as valid matches.\n"
        "- Evaluate the correctness of the prediction compared to the answer."
    },
    {
      "role": "user",
      "content":
        "Please evaluate the following video-based question-answer pair:\n\n"
        f"Question: {question}\n"
        f"Correct Answer: {answer}\n"
        f"Predicted Answer: {pred}\n\n"
        "Provide your evaluation only as a yes/no and score where the score is an integer value
        between 0 and 5, with 5 indicating the highest meaningful match. "
        "Please generate the response in the form of a Python dictionary string with keys 'pred' and
        'score', where value of 'pred' is  a string of 'yes' or 'no' and value of 'score' is in INTEGER, not
        STRING."
        "DO NOT PROVIDE ANY OTHER OUTPUT TEXT OR EXPLANATION. Only provide the Python
        dictionary string. "
        "For example, your response should look like this: {'pred': 'yes', 'score': 4.8}."
    }
  ]
)
```

Figure A1. Prompt for ChatGPT in LLM-Assisted Evaluation.