BAMBOO: A Comprehensive Benchmark for Evaluating Long Text Modeling Capacities of Large Language Models

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Abstract

Large language models (LLMs) have achieved dramatic proficiency over NLP tasks with normal length. Recently, multiple studies have committed to extending the context length and enhancing the long text modeling capabilities of LLMs. To comprehensively evaluate the long context ability of LLMs, we propose **BAMBOO**, a multi-task long context benchmark. BAMBOO has been designed with four principles: comprehensive capacity evaluation, avoidance of data contamination, accurate automatic evaluation, and different length levels. It consists of 10 datasets from 5 different long text understanding tasks, i.e., question answering, hallucination detection, text sorting, language modeling, and code completion, to cover core capacities and various domains of LLMs. We conduct experiments with five long context models on BAMBOO and further discuss four key research questions of long text. We also qualitatively analyze current long context models and point out future directions for enhancing long text modeling capacities. We release our data, prompts, and code at https://github.com/RUCAIBox/BAMBOO.

1 Introduction

Recently, large language models (LLMs) have exhibited huge success across a wide range of NLP tasks (Ouyang et al., 2022; Touvron et al., 2023a; Zhao et al., 2023). Despite their remarkable capacity, existing LLMs remain restricted by limited context length, suffering from performance decline when the input text exceeds their length limit. To enhance the capability of LLMs to model long texts, several studies extend the context window through position interpolation (kaiokendev, 2023; Chen et al., 2023; Peng et al., 2023), and continuing to fine-tune the models on multi-turn conversations and long text datasets (Zheng et al., 2023). Moreover, several research also explores transforming the original long text into short texts

within the context length based on recurrence or compression techniques (Zhou et al., 2023).

To push forward the research of long context modeling, it is important to develop an automatic, reliable, and comprehensive evaluation benchmark specially for assessing LLMs' performance on long-text based tasks. In existing literature, several benchmarks have been proposed to evaluate the long context modeling ability of LLMs, such as ZeroSCROLLS (Shaham et al., 2023), L-Eval (An et al., 2023), and LongBench (Bai et al., 2023). However, an important aspect that has been ignored by these studies is the potential data contamination issue (Golchin and Surdeanu, 2023), which means that there might exist overlaps between the pretraining data and evaluation data. Further, some tasks in these benchmarks can not be accurately evaluated by automatic metrics (Wang et al., 2023), making it difficult to reproduce and compare the results of large models exactly.

We propose **BAMBOO**, a comprehensive benchmark to analyze LLMs' long text modeling. Our BAMBOO benchmark comprises ten datasets from five tasks, including question answering, hallucination detection, text sorting, language modeling, and code completion. In our benchmark, salient information is spread throughout the complete long texts, thus the LLM needs to model long-range dependencies to solve these tasks according to the instructions. BAMBOO can comprehensively evaluate language generation, knowledge utilization, reasoning, and tool manipulation abilities over long text. The model needs to model both the coarsegrained information related to the macro comprehension of the complete text and fine-grained information about details across several sentences. Moreover, with datasets from multiple domains, BAMBOO can access LLMs' understanding abilities across different sources.

Our BAMBOO benchmark is divided into two subsets at different length level, *i.e.*, BAMBOO-4k

and BAMBOO-16k, according to the number of tokens in the prompt ¹. The 4k and 16k subsets each contain 1442 samples, with average lengths of 2310 and 6586 words, respectively. To alleviate the data contamination issue, our benchmark is constructed based on the data sources that are released in 2023. Furthermore, we select diverse tasks with accurate automatic metrics. Table 1 presents a comparison of our benchmark with existing benchmarks.

Benchmark	ZeroSCROLLS	L-Eval	LongBench	BAMBOO
Accurate Evaluation	×	×	×	✓
Avoidance of Data Contamination	×	×	×	✓
Different Length Levels	×	×	✓	✓
#Len	9324	7271	6711	4148
#Tasks	3	4	6	5

Table 1: Comparison with other long context benchmarks. #Tasks and #Len denotes the number of tasks and average length respectively.

We extensively evaluate five long context LLMs on the BAMBOO benchmark. We observe that ChatGPT-16k shows optimal performance over most datasets, while other models usually struggle, especially on unfamiliar tasks. In addition, input with longer texts often lead to performance drops. We further conduct a series of analysis experiments to discuss key questions of long text modeling. When adapting models for long texts, they can better deal with longer text tasks but fail in shorter text tasks, which is an "extension tax". Furthermore, the optimal position of task instructions varies depending on the model, dataset, and input length. Small models may suffer catastrophic forgetting of instructions when we only locate the instructions at the beginning of long input. Instead of these challenges of long lengths, the poor performances may be mainly owing to insufficient reasoning abilities of existing LLMs. Moreover, proper context compression techniques, which enables models to process part of the long texts at once, is a shortcut for modeling long texts. In the end, we make a qualitative analysis over long context LLMs about instruction forgetting, format errors, reasoning, and abnormal long text tasks. Accordingly, we point out future directions to enhance the long text modeling abilities of LLMs.

2 Related Work

Long Context Architecures Owing to the quadratic memory and computational complexity of self-attention, original Transformer models could hardly scale to an extended context. To make Transformers more efficient, multiple improvements over the attention mechanism were explored. Transformer-XL (Dai et al., 2019) and Compressive Transformers (Rae et al., 2020) split a long text into multiple segments, sequentially modeled each segment, and re-used the past segments' activations in the subsequent segment. Longformer (Beltagy et al., 2020) and Big Bird(Zaheer et al., 2020) employed fixed attention patterns, restricting the attention only to the local tokens. Similarly, Reformer (Kitaev et al., 2020) and Routine Transformer (Roy et al., 2021) learned to split tokens in baskets and made each token only accessible to other tokens in the same basket. Different from limiting the length of tokens could be attended to, several methods approximated the multiplication of attention matrices through low-rank (Wang et al., 2020; Ma et al., 2021) or kernel-based methods (Katharopoulos et al., 2020; Peng et al., 2021). In addition to the above Transformer variants, various models replacing attention with other modules were proposed. S4 (Gu et al., 2022), DSS (Gupta et al., 2022), and GSS (Mehta et al., 2023) employed State Space Models, while RetNet (Sun et al., 2023) utilized retention mechanism, achieving parallel training and recurrent inference for long sequences.

Adapting LLMs for Long Context Recently, with the booming of large language models, a series of work focused on solving long context tasks with LLMs. Several research studies explored how to break the length limitations of Transformers without modifying their architectures. Inspired by fusion-in-decoder (Izacard and Grave, 2021), PCW (Ratner et al., 2023) separately encoded different chunks in a long text with the same position encodings and all the hidden states were visible during the generation process. Unlimiformer (Bertsch et al., 2023) and Focused Transformer (Tworkowski et al., 2023) retrieved top-k relevant tokens from cached external memories for each token, achieving near unlimited context length. Furthermore, a series of studies attempted to directly extend the context windows of LLMs with RoPE (Su et al., 2021) positional embeddings

¹All references to the number of tokens in our paper are calculated by tokenizer of gpt-3.5-turbo.

via Position Interpolation (kaiokendev, 2023; Chen et al., 2023; Peng et al., 2023). Meanwhile, another direction worth exploring is modeling long text with short-context models through the context compression mechanism. ChatPDF ² first retrieved paragraphs related to the question and sent the question as well as the retrieved context as the prompt to ChatGPT for the answer. RecurrentGPT (Zhou et al., 2023) simulated the recurrence mechanism in LSTM with language prompts, iteratively generating long text without forgetting the past information.

Evaluation for Long Text Modeling For evaluating the long text modeling capability, a wide range of datasets was proposed, mainly divided into three types of tasks, i.e., language modeling, question answering, and summarization. Language modeling was the early major long text task with the objective to sequentially predict the next tokens based on previous ones (Rae et al., 2020). However, most tokens only needed modeling a limited context instead of long-term relations (Sun et al., 2021). Long text summarization task could be divided into normal summarization (Cohan et al., 2018; Huang et al., 2021; Chen et al., 2022) and query-based summarization (Zhong et al., 2021), where the model summarized the whole or part of long texts into their summaries. In question answering, the input usually contained multiple documents (Yang et al., 2018) or a single long document (Pang et al., 2022; Dasigi et al., 2021). Now, the latter two tasks are classic evaluations evaluating different granularity of long text modeling ability.

To make a comprehensive evaluation of the models' long text modeling ability, some long text benchmarks were released. Long Range Arena (Tay et al., 2021) was the first long sequence benchmark over data from different modalities. To extend input length, byte-level text tasks were employed, which were not suitable for evaluating token-level LLMs. SCROLLS (Shaham et al., 2022) collected long text reasoning datasets from different tasks and domains and standardized them into a text-to-text format. Recently, with LLM drawing a great deal of attention, ZeroSCROLLS (Shaham et al., 2023), L-Eval (An et al., 2023), and LongBench (Bai et al., 2023) were released, focusing on the zero-shot long text comprehension ability of LLMs. However, there

were potential data contamination problems, and some datasets could not be accurately evaluated through automatic metrics.

3 BAMBOO Benchmark

Our BAMBOO benchmark commits to fairly and comprehensively evaluating LLMs' long text modeling ability. We elaborately construct ten diverse datasets with a unified input and output format covering a wide range of domains to examine different abilities of long context understanding. The overview of the BAMBOO benchmark is shown in Table 2.

3.1 Design Principles

Different from existing long text benchmarks in Table 1, our BAMBOO benchmark is designed to comprehensively evaluate the long text modeling capacity of LLMs. Our benchmark can potentially circumvent the issue of pre-training data contamination in previous benchmarks, pursue more accurate automatic evaluation, and cater to LLMs at different length levels.

Comprehensive Capacity Evaluation BAM-BOO is constructed with the primary goal of comprehensively evaluating long text modeling abilities of LLMs with different tasks and domains. To meet the real need in long text scenarios, all the tasks assess the ability to model long-range dependencies. Inspired by Zhao et al. (2023), we consider diverse tasks evaluating language generation, knowledge utilization, reasoning, and tool manipulation capacities over long texts in BAMBOO. BAMBOO can also evaluate the coarse-grained comprehension of the complete texts and the fine-grained reasoning over detailed information. Moreover, we collect data from various sources, assessing and comparing abilities over different domains.

Avoidance of Data Contamination We attempt to minimize the overlap between test data and the training corpora of LLMs as much as possible in BAMBOO. When evaluating the long text understanding capability of LLMs, a potential issue is that the model has "seen" the input text during the pre-training or fine-tuning stages, *i.e.*, data contamination. To alleviate this issue, we only preserve data released in 2023, since the training data of ChatGPT and Claude2 are up to September 2021³

²https://www.chatpdf.com

³https://platform.openai.com/docs/models/ gpt-3-5

Dataset	#Len	#Example	Metric	Domain	Source
AltQA	2297/8320	200/200	accuracy	Wikipedia	https://github.com/abacusai/long-context
PaperQA	2330/4866	40/40	accuracy	Paper	https://aclanthology.org/
MeetingQA	2195/7951	100/100	accuracy	Meeting	https://record.assembly.wales/
SenHallu	2297/4619	200/200	P/R/F1	Paper	https://aclanthology.org/
AbsHallu	2415/4699	200/200	P/R/F1	Paper	https://aclanthology.org/
ShowsSort	2046/4506	200/200	CI	TV Shows	https://tvmeg.com/
ReportSumSort	3753/8309	150/150	CI	Reports	https://www.gao.gov/
ShowsPred	1771/3641	100/100	accuracy	TV Shows	https://tvmeg.com/
MeetingPred	2960/9313	100/100	accuracy	Meeting	https://record.assembly.wales/
PraviteEval	1701/3376	152/152	pass@1	Code	https://github.com/microsoft/PyCodeGPT

Table 2: Overview of our BAMBOO benchmark. #Len and #Example represent the average length of inputs and the number of examples of each dataset, respectively. For #Len and #Example, "number1/number2" is the number of the middle and long versions, respectively. P/R/F1 denotes precision/recall/F1, and CI stands for concordance index.

and the early 2023⁴. However, owing to the unknown of the training data of some models, we cannot promise there are no data sources employed for training in our benchmark. In addition, we also utilize datasets with modified input keywords and answers, forcing the model to give a response based on the input.

Accurate Automatic Evaluation In our benchmark, each task can be precisely evaluated in an automatic manner, as our constructed tasks have standardized answers and can be measured by metrics such as accuracy, F1, pass@1, etc. Previous benchmarks include certain natural language generation tasks (e.g., text summarization and question answering), and the responses generated by LLMs may have a different expression from the reference answers, making it difficult to accurately evaluate their outputs with automatic metrics (Tang et al., 2023), even using LLMs as evaluator (Wang et al., 2023). Hence, we transform some generation tasks into multi-choice tasks and select tasks that can be precisely evaluated.

Different Length Levels Finally, each task in our benchmark has two different length levels. The most popular LLMs, *e.g.*, ChatGPT⁵ and Llama2 (Touvron et al., 2023b), only have a context window of 4k tokens while some of them have been extended to contain 16k or more tokens, including ChatGPT-16k⁵ and ChatGLM2-6b-32k (Zeng et al., 2023). However, due to the different length distributions of different datasets, it is difficult to analyze the impact of length changes on LLMs in

the same task, which has not been considered in previous benchmarks. Thus, we divide each task in our benchmark into two subsets based on the input length, with the maximum length of 4k and 16k, respectively. Thus, we can better measure the impact of the length of input texts, the context window of LLMs, *etc*.

3.2 Data Collection

To ensure a diverse range of domains, we collect long texts from four distinct sources, including NLP research papers, government reports, transcripts of TV shows, and transcripts of committee meetings. These data sources are all publicly available and released in 2023 to avoid pre-training data contamination. We crawled the source websites and parsed them, extracting only the plain text while discarding images, tables, and footnotes. Then, we filtered texts with less than 1000 tokens and truncated texts with extended lengths. In addition to these latest corpora, we also construct pseudo corpus consisting of long texts with modified input keywords and answers.

To achieve the goal of diverse length levels, we divided samples in BAMBOO benchmark into two subsets based on the length of the complete input text. One subset contains prompts up to 4k tokens (called BAMBOO-4k), while the other subset consists of prompts with tokens from 4k to 16k (called BAMBOO-16k).

3.3 Task Construction

We aim to evaluate long text modeling ability in BAMBOO comprehensively. To achieve the objective, we constructed five tasks and ten datasets based on the first principle.

⁴https://efficient-manatee.files.svdcdn.com/ production/images/Model-Card-Claude-2.pdf

⁵https://chat.openai.com/

Question Answering In the question answering task, we mainly evaluate knowledge utilization and reasoning ability. For question-answering tasks, we manually construct two multi-choice question answering datasets, PaperQA and MeetingQA, by human labelers to evaluate the LLMs' ability to understand a long document or dialogue. The expressions of questions and options are reorganized instead of directly employing the original formulations. And most of the answers are reasoned from evidence in multiple paragraphs. In addition, we also apply the altered numeric QA dataset (AltQA (Pal et al., 2023)), consisting of multiple documents from Wikipedia, along with a corresponding question. Each question can be answered by a number, and every occurrence of the answer within the documents is modified to avoid it being answered by memorized data.

Hallucination Detection Hallucination is a common occurrence in LLMs, i.e., the generated content may conflict with or be beyond the source. The model must employ the knowledge of given contexts to detect hallucinations in the task. By ChatGPT generating hallucinations based on the correct hypothesis (e.g., a few words modification or a make-up sentence insertion) (Li et al., 2023b), We create two novel datasets, i.e., SenHallu and AbsHallu, to evaluate hallucination on long text. Based on the idea of natural language inference tasks, we present LLMs with the original paper as the premise along with a hypothesis, which may be either true or false. Subsequently, we request LLMs to judge whether the summary entails or contradicts the paper content as a binary classification task.

Text Sorting To evaluate whether the model can reasoning over the logical order of texts, we create two text sorting datasets that require LLMs to reorder the shuffled texts with contextual information of the whole texts. **ShowsSort** is a sorting task over shuffled text segments. Given permuted consecutive segments of a TV show transcript, the goal is to restore these segments to their original order according to the contextual continuity and the meaning of each segment. **ReportSumSort** is another sorting task with the input of a whole government report and a list of shuffled summaries. The objective is to reorder these summaries according to the positions of the segments represented by them in the report.

Language Modeling Language modeling task is a typical language generation task that needs to predict the next token based on the past context. However, most tokens can be predicted in practice based on a limited context window. In order to evaluate the long-range dependencies, we designed the task intending to predict the last turn of the conversation's speaker with a long dialogue. To be specific, we adopted multiple turns of conversations as the source and formatted each utterance as "{utterance} said by {speaker}". Then, we remove the speaker of the last turn as the target to be predicted. To predict the speaker, the model typically needs to understand the characteristics of existing speakers and the contextual conversations. We constructed **ShowsPred** and **MeetingPred** with transcripts of TV shows and meetings as sources, respectively.

Code Completion To solve complicated tasks, LLMs typically need to manipulate tools through API calls. To evaluate whether an LLM can recognize the target tools from irrelevant ones and synthesis code with the documents, we construct the PrivateEval dataset on the basis of the benchmark from Zan et al. (2022). Given API documents from private libraries and a code snippet, the goal is to complete the code. Therefore, the model needs to identify key API documents and complete the code with the relevant documents. We manually modified the keywords in API documents of the Torchdata library as previous modifications in the Monkey and BeatNum libraries. Furthermore, we changed the number of the provided documents for length control.

4 Experiment

With BAMBOO benchmark, we conduct experiments of long context LLMs to evaluate their zero-shot long text modeling capability. We further discuss key questions of long text modeling and give a qualitative analysis.

4.1 Baselines

We select five instruction-tuned models with a context length of over 16k tokens as our baselines. For the Closed models available through API, we select gpt-3.5-turbo-16k⁵ from OpenAI and Claude2-100K⁶ from Anthropic. For open-sourced models, we select Vicuna-7b-v1.5-16k (Zheng et al.,

⁶https://www.anthropic.com/index/claude-2

M. J.L.	ShowsSort		ReportSumSort		ShowsPred		MeetingPred		SenHallu	
Models	16k	4k	16k	4k	16k	4k	16k	4k	16k	4k
gpt-3.5-turbo-16k	59.0	58.2	69.6	77.6	55.0	53.0	57.0	73.0	62.7/99,0/76.7	68.1/96.0/79.7
Claude2-100k	53.1	54.0	59,7	66.7	8.0	26.0	0.0	21.0	67.3/99.0/80.2	69.3/97.0/80.8
ChatGLM2-32k	32.0	42.7	31.6	43.5	13.0	8.0	14.0	25.0	52.9/100.0/69.2	52.7/96.0/68.1
Vicuna-v1.5-16k	53.2	53.6	50.1	51.4	5.0	11.0	5.2	64.0	56.4/92.9/70.2	67.7/99.0/69.3
Longchat-v1.5-16k	53.2	53.8	44.5	47.9	1.0	1.0	29.9	36.0	50.3/100.0/66.9	51.2/100.0/67.8
Random Results	50.0	50.0	50.0	50.0	7.6	10.3	8.0	13.9	50.0/50.0/50.0	50.0/50.0/50.0
	PrivateEval AltQA		PaperQA MeetingQA		AbsHallu					
Models	16k	4k	16k	4k	16k	4k	16k	4k	16k	4k
gpt-3.5-turbo-16k	21.7	21.1	72.0	76.5	67.5	70.0	72.0	75.0	55.6/100.0/71.4	57.2/99.0/72.5
Claude2-100k	0.7	7.2	4.5	27.0	50.0	65.0	47.0	63.0	56.8/100.0/72.5	58.2/99.0/73.3
ChatGLM2-32k	3.5	0.7	67.0	64.0	57.5	61.5	65.0	52.0	50.5/100.0/66.7	50.0/99.0/66.4
Vicuna-7b-v1.5-16k	2.0	3.3	25.0	30.5	52.5	32.5	27.0	31.0	51.0/99.0/67.3	53.3/88.0/66.4
Longchat-7b-v1.5-16k	0.7	3.9	41.7	64.0	37.5	47.5	36.0	42.0	50.3/100.0/66.9	50.0/100.0/66.7
Random Results	0.0	0.0	0.0	0.0	25.0	25.0	25.0	25.0	50.0/50.0/50.0	50.0/50.0/50.0

Table 3: Results (%) of selected long context LLMs on our benchmark. We report both the performance on 4k and 16k versions of all datasets. For SenHallu and AbsHallu, we sequentially exhibit precision, recall, and F1.

2023), Longchat-7b-v1.5-32k (Li et al., 2023a), and ChatGLM2-6b-32k (Du et al., 2022; Zeng et al., 2023) ⁷.

We add a random baseline for each task. For text sorting and language modeling tasks, we randomly return the permutated sequences and pre-existing speakers in the dialogues, respectively. For hallucination detection and multi-choice QA datasets, we randomly select one choice from (true, false) or (A, B, C, D). For PrivateEval and AltQA, we directly set the random baseline to 0 due to the infinite search space for answers.

4.2 Metrics

As shown in Table 1, we employ four different metrics to evaluate different tasks in our benchmark, *i.e.*, accuracy for question answering and language modeling, concordance index for sorting, pass@1 for code completion and precision, recall, and F1 for hallucination detection. All the answers are generated freely, and we directly regard the answers with a wrong format as false.

• Accuracy: we collect the first words for question answering and the first paragraphs for language modeling and filter irrelevant words. Then we compare them to the reference and count the proportion of right answers.

- Concordance Index: for the sorting task, the answer is a list of identifiers of segments. For each pair in the list, we compare whether its the same order in the real list. The concordance index is the number of pairs with correct orders divided by the total amount of pairs (Shaham et al., 2023).
- Pass@1: following Zan et al. (2022), we provide one snippet for each program to be completed and count the percentages of correct samples.
- Precision/Recall/F1: for the binary classification tasks, the precision and recall respectively evaluate the true positives over predicted positives and real positives. F1 is the harmonic mean of precision and recall. These metrics can better evaluate imbalanced hallucination detection.

4.3 Overall Results

The overall results for the performance of each model on the BAMBOO benchmark are presented in Table 3. Across different datasets and length levels, we can observe that ChatGPT-16k shows general and splendid performance, greatly outperforming other models over almost all tasks except a slight gap on the hallucination detection task. However, the performances of other models are usually poor, even worse than random baselines.

Moreover, we find that models usually fail at datasets with abnormal objectives and complex requirements, even the most powerful ChatGPT. When it comes to hallucination detection tasks

⁷We abbreviate gpt-3.5-turbo as ChatGPT, Vicuna-7b-v1.5 as Vicuna, Claude2-100k as Claude2, Longchat-7b-v1.5 as Longchat, and ChatGLM2-6b as ChatGLM2 in the following.

where there are only minor differences between the hallucinated and the correct hypothesis, most LLMs can hardly capture those hallucinations, demonstrating low precision. In addition, LLMs also underperform in ShowsSort and PrivateEval, highlighting their inability to aggregate, manipulate tools, and synthesize code. It can be inferred that the narrowness of training data types is partly a reason for the poor performances.

Comparing performances over different length levels, we observe that for most datasets and models, the performances drop as the input lengths extend, especially for those tasks where the model must identify salient information from many irrelevant segments.

4.4 Key Questions of Long Text Modeling

As shown in Table 3, current LLMs have limited long-text comprehension abilities, and even gpt-3.5-turbo-16k performs poorly on some tasks. In the following section, we mainly focus on four questions in the long text modeling tasks: (1) Do LLMs with long context windows pay for extension tax? (2) How do instruction positions affect long text modeling? (3) To what extent do LLMs struggle due to the long input? (4) Can LLMs model longer text with context compression methods?

RQ1: Do LLMs with Long Context Windows Pay for Extension Tax?

We first discuss whether extending the LLMs' context windows and fine-tuning LLMs on long texts harm performance over tasks with shorter texts. We compared ChatGPT-16k and Vicuna-16k to their regular-context-length variants on selected tasks from BANBOO-middle and MMLU (Hendrycks et al., 2021).

Model	SHallu	AQA	MPred	RSSort	MMLU
ChatGPT-16k	79.7	76.5	73.0	77.6	-
ChatGPT	79.3	76.5	72.0	77.3	70
Vicuna-16k	69.3	30.5	64.0	51.4	48.5
Vicuna	66.0	52.0	11.0	18.2	49.8

Table 4: Results of normal length models and its extended variants on selected datasets-4k and MMLU. We abbreviate SenHallu as SHallu, AltQA as AQA, MeetingPred as MPred, and ReportSumSort as RSSort. For each dataset, we only evaluate the performance over the 4k subset. We only show F1 scores for SenHallu.

As shown in Table 4, ChatGPT and Vicuna exhibit different trends. Performances between Chat-

GPT and its 16k variant over different tasks are almost identical. However, we can observe a dropped performance on MMLU after replacing Vicuna with Vicuna-16k. The longer training data and position interpolation have undoubtedly harmed the ability on normal-length tasks, which is an "extension tax". Furthermore, the Vicuna without an extended context window even performs worse in BAMBOO-middle, indicating it is badly adapted to length close to its maximum length, and longer training data can benefit performance over relevantly short texts.

RQ2: How Do Instruction Positions Affect Long Text Modeling?

Since LLMs are sensitive to the prompt, we explore the impact of the position of instruction on long text tasks. Specifically, We divided the complete prompt into two parts. One is the context that contains the content of the given long text (denoted as C), while the other is the instruction that contains task descriptions and optional questions, summaries, hypotheses, etc (denoted as I). We redesigned prompts and located the instruction in different positions relative to the context.

We can compare the impact of instruction position on Table 5. The best instruction positions vary from the input length, datasets, and model. In MeetingPred, it's better only to put the instruction at the beginning of the prompt, keeping the consecution of language modeling tasks. However, for ShowsSort, which has a complex demand of tasks and format, we may find that performance drops when there is no instruction at the end. It may be due to cataclysmic forgetting the demands after reading the long texts.

RQ3: To What Extent Do LLMs Struggle Due to The Long Input?

To evaluate the long text modeling ability, an important question is whether the difficulty is attributed to the long texts or the capacity to solve the task. In certain tasks, only short golden evidence is helpful, while other segments in the long text may distract from the answer. Thus, we only prompt the evidence to the model instead of providing the complete text in MeetingQA, PaperQA, and PrivateE-val.

As shown in Table 6, we can observe generally improved performance on different datasets. The mislocalization of evidence in long text partly causes errors. However, a more important obser-

Madal	D:'4'	ShowsSort		SenI	MeeetingPred		
Model	Position	16k	4k	16k	4k	16k	4k
	I+C	54.5	56.4	62.7/99.0/76.7	68.1/96.0/79.7	20.5	45.0
ChatGPT-16k	C + I	55.4	54.6	61.0/100.0/75.8	64.2/97.0/77.3	9.5	16.0
	I + C + I	54.6	60.2	61.0/100.0/75.8	61.8/97.0/75.5	16.0	29.0
	I+C	42.8	52.4	50.0/100.0/66.7	54.7/99.0/70.5	5.0	24.0
Vicuna-16K	C + I	51.4	53.9	51.9/98.0/67.8	64.0/87.0/73.7	13.0	2.0
	I + C + I	52.4	53.5	52.8/95.0/67.9	66.3/67.0/66.7	12.0	8.0
	I + C	42.6	45.4	53.2/99.0/69.2	53.8/98.0/69.5	13.0	18.0
ChatGLM2-32k	C + I	29.2	45.65	53.5/100.0/69.7	55.2/100.0/71.2	8.0	11.0
	I + C + I	37.8	47.5	53.2/100.0/69.4	51.6/99.0/67.8	12.0	15.0

Table 5: Results of LLMs with three different positions of instruction relative to content. I + C and C + I represents put the instruction before and after and content respectively. I + C + I denotes insert instruction at both ends of the content.

vation is the improvements are very minor, and Vicuna's performance even drops in PaperQA. In addition, we find that the model tends to make the same mistake in both settings. Therefore, we infer that the awful performances of LLMs are mainly due to poor reasoning and coding ability instead of localization evidence in the long text.

		MeetingQA		PaperQA		PrivateEval	
Models	Input	16k	4k	16k	4k	16k	4k
ChatGPT-16k	evidence complete		78.0 75.0				31.6 21.1
Vicuna-16k	evidence complete	40.0 27.0	36.0 31.0	40.0 52.5	30.0 32.5	5.3 2.0	5.3 3.3

Table 6: Comparison of LLMs' performances with the input of only golden evidence or the complete text.

RQ4: Can LLMs Model Longer Text with Context Compression Methods?

Though there are multiple long context models, the mainstream models can only process up to 4k tokens, and the computational and memory burdens increase quadratically with the length. Thus, a promising direction is to employ normal LLMs to model long texts with context compression techniques, *e.g.*, retrieval, and truncation.

Previous work has attempted to employ these techniques to solve long text tasks with pretrained language models (Gong et al., 2020; Zhang et al., 2022; Zhao et al., 2022). To meet the differences across datasets, we separately design a naive context compression method for each dataset. In PrivateEval, we choose the documents from the library that appear in the code to be completed and retrieve the top-5 relevant documents with

APIRetriever (Zan et al., 2022). In AltQA, We retrieved the top-5 relevant segments with DPR retrievers (Karpukhin et al., 2020). In ShowsSort, we summarize each segment and ask the model to reorder shuffled summaries. Meanwhile, we only keep the content of the Introduction subsection for SenHallu and the last ten turns of conversations for MeetingPred. We compare the performance of ChatGPT and Vicuna with these compression techniques to ChatGPT-16k and Vicuna-16k.

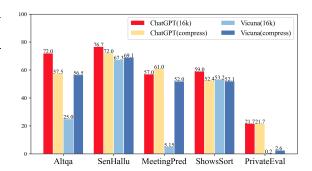


Figure 1: Comparisons between models with context compression techniques with their long context variants. For SenHallu, we only exhibit the F1 scores of each model.

The comparison between normal context LLMs with compression techniques and long context LLMs is shown in Figure 1. For ChatGPT, we can observe a compression incurs performance in most datasets. Despite avoiding interference of some irrelevant information, some salient information may also be dropped, and the remaining irrelevant information may be more harmful. Additionally, opposite trends are shown for Vicuna that may not follow instructions and understand long

prompts well. In addition, with the proper compression technique for datasets, the performances are higher in MeetingPred. To some extent, compression techniques can bring shortcuts to solving long texts with normal models, yet their effects are limited to information preservation and adaptation to tasks. We believe more powerful compression approaches may make this technique more efficient and effective.

4.5 Qualitative Analysis and Discussions

Finally, we give a qualitative analysis of the performance of LLMs over long texts.

- A severe problem is the cataclysmic forgetting of instructions. We can usually observe the generating responses that do not match the task demands. During the generation process, the instruction may be forgotten or even not understood at all, especially if the instruction is put at the beginning of the very long input. Models with small scales are more likelier to obey the instructions, which may be due to insufficient memorization and instruction understanding abilities. Thus, a promising direction is to enhance the instruction-following ability of long-context models via more robust instruction datasets in the future.
- LLMs are prone to format errors in long text tasks. Through analyzing the generations, we observe that the predictions may be in an informal format though they express the same meaning as the references, which can not be identified during the evaluation. The models may respond to us with additional descriptions, repetitions, or in a different format. This is an important reason for the awful results of certain models, *e.g.*, Claude2-100k. To alleviate the problem, we suggest employing post-process techniques to rewrite the response to our expected format. We also suggest reducing the format problems during the fine-tuning or RLHF stages.

• LLMs exhibit poor performance on reasoning. Despite understanding instructions and format, the LLM may still generate false responses to the long input. Even provided with golden evidence in question answering tasks, the performance may still not be improved at all. This error can be attributed to insufficient ability of reasoning, which is universal across different lengths and tasks. Therefore, it is important to make an enhancement to the overall reasoning abilities of LLMs instead of only focusing on long text domains.

• LLMs perform poorly on abnormal tasks.

As shown in Table 3, we can find that LLMs generally have an awful performance on tasks that are not common, *e.g.*, text sorting and code completion, even underperformed by random baselines. We found that most of the open-sourced models were fine-tuned on instruction data belonging to conversation, question answering, and summarization tasks. Due to the narrowness of training data, LLMs can not generalize well to long text tasks unfamiliar. We believe that broadening the variety of tasks and domains on fine-tuning data can better comprehensively enhance LLMs' long text modeling capacities.

5 Conclusion

We propose BAMBOO, a benchmark for comprehensively evaluating the long text modeling capabilities of LLMs. BAMBOO consists of five tasks with two length levels, enabling the evaluation of LLMs' main capacities across various dimensions and domains. Based on the evaluation of several long context models on BAMBOO, we give an overall analysis of the performances of different models and tasks. We have discussed key questions of long text models, provide a qualitative analysis of long text modeling tasks, and suggest directions for improving long context modeling abilities. We believe BAMBOO can be employed to analyze the extensive capacities and advance the long text modeling proficiency of LLMs in the future.

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