Long-context LLMs Struggle with Long In-context Learning

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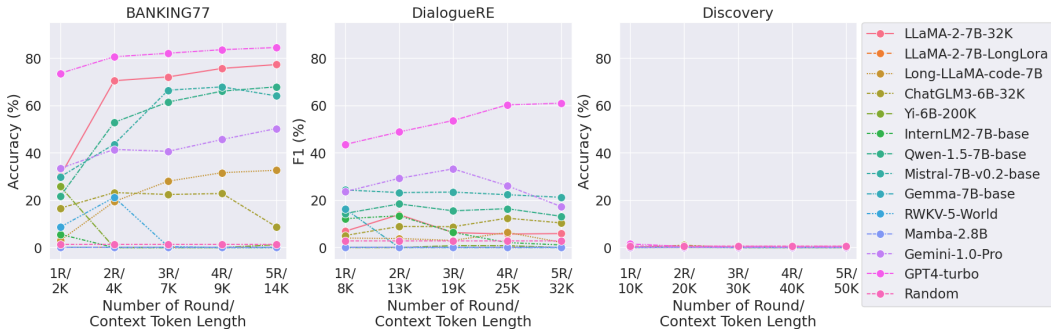https://github.com/TIGER-AI-Lab/LongICLBench

Figure 1: LLM performance on long in-context benchmark across different lengths. We curate datasets with different difficulty levels. As we increase the difficulty of the dataset, LLMs struggle to understand the task definition and suffer from significant performance degradation. On the most difficult Discovery dataset, none of the LLMs is able to understand the long demonstration, leading to zero accuracy.

Abstract

Large Language Models (LLMs) have made significant strides in handling long sequences exceeding 32K tokens. However, their performance evaluation has largely been confined to metrics like perplexity and synthetic tasks, which may not fully capture their abilities in more nuanced, real-world scenarios. This study introduces a specialized benchmark (*LongICLBench*) focusing on long in-context learning within the realm of extreme-label classification. We meticulously selected six datasets with a label range spanning 28 to 174 classes covering different input (few-shot demonstration) lengths from 2K to 50K tokens. Our benchmark requires LLMs to comprehend the entire input to recognize the massive label spaces to make correct predictions. We evaluate 13 long-context LLMs on our benchmarks. We find that the long-context LLMs perform relatively well on less challenging tasks with shorter demonstration lengths by effectively utilizing the long context window. However, on the most challenging task Discovery with 174 labels, all the LLMs struggle to understand the task definition, thus reaching a performance close to zero. This suggests a notable gap in current LLM capabilities for processing and understanding long, context-rich sequences. Further analysis revealed a tendency among models to favor predictions for labels presented toward the end of the sequence. Their ability to reason over multiple pieces in the long sequence is yet to be improved. Our study reveals that long context understanding and reasoning is still a challenging task for the existing LLMs. We believe *LongICLBench* could serve as a more realistic evaluation for the future long-context LLMs.

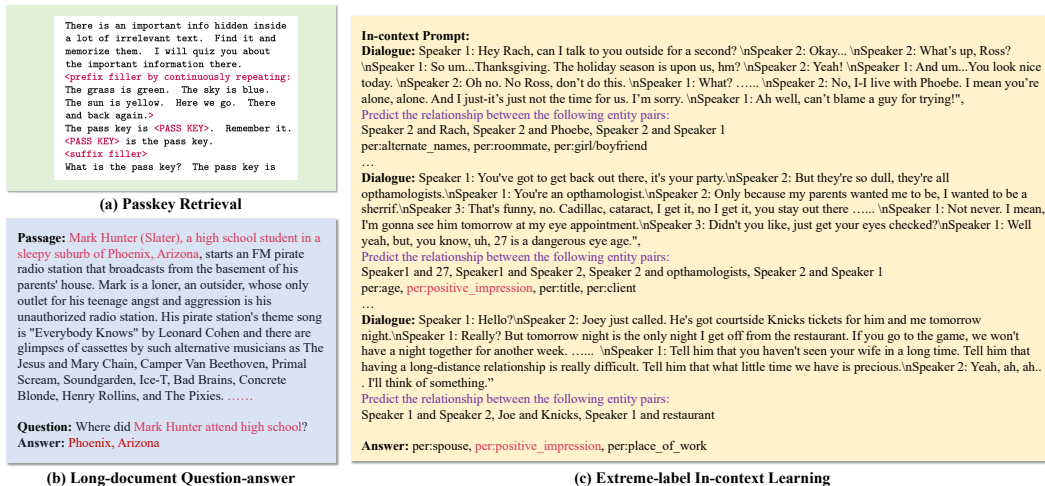arXiv:2404.02060v1 [cs.CL] 2 Apr 2024

Figure 2: Comparison extreme-label ICL with the existing evaluation tasks. Passkey Retrieval is a synthetic task. Long-document Question-answering does not require reading the entire document to find the answer. In extreme-label ICL, the model needs to scan through the entire demonstration to understand the whole label space to make the correct prediction.

1 Introduction

Large language models have already entered the long context era. Myriad of LLMs has been released to support long context windows from 32K to 2M tokens. These methods (Hao et al., 2022; Chen et al., 2023a; Peng et al., 2023b; Ratner et al., 2023; Xiao et al., 2024) can unlock lots of complex real-world applications from long-document question-answering, multi-document summarization, long-horizon agent tasks, repo-level code understanding.

One line of research is based on AliBi (Press et al., 2022) and RoPE (Su et al., 2024) embedding, which allows us to train Transformers with short sequences and subsequently apply them to longer sequences during inference. Recently, different approaches (Xiong et al., 2023; Fu et al., 2024; Liu et al., 2024) help the model to extrapolate to 128K window size with continued pre-training. Later on, LongRoPE (Ding et al., 2024) was proposed to further extend to the context window to 2M tokens. Another line of research also utilizes methodologies like context window sliding and segmentation to overcome the issue of the limited context window in original Transformers (Hao et al., 2022; Ratner et al., 2023). Furthermore, architectural innovations, transitioning from traditional Transformer-based designs to recurrent models or state space models, have shown promise in facilitating long-range computations naturally Orvieto et al. (2023); Gu & Dao (2023); Peng et al. (2023a). These techniques have been incorporated into several current open-source LLMs to enhance long sequence understanding capability (Chen et al., 2023b; Tworkowski et al., 2023).

These long-context models are primarily evaluated on three types of evaluations:
1. language model perplexity over long documents, which is used by most papers.
2. passkey retrieval (Mohtashami & Jaggi, 2023; Chen et al., 2023a; Li et al., 2023a) or needle-in-a-haystack (Team et al., 2023; Fu et al., 2024), which requires reciting a randomly inserted information in a long sequence. Several LLMs achieve 99%+ on this synthetic task.
3. long-document question-answer or summarization over Qasper (Dasigi et al., 2021).

Evaluations (1) and (2) only provide a minimum bar for LLMs to pass, but their results cannot reflect LLMs' true ability to deal with realistic long-sequence tasks. Evaluation (3) provides a more realistic metric, however, these tasks are more focused on retrieving correct information from the long input. In question answering, LLMs can take shortcut to read a short snippet to predict the answer without reading the entire document as demonstrated in Figure 2 case (b). Similarly, summarization also suffers from the strong position bias, where LLMs can utilize the few leading sentences (Nallapati et al., 2017) to
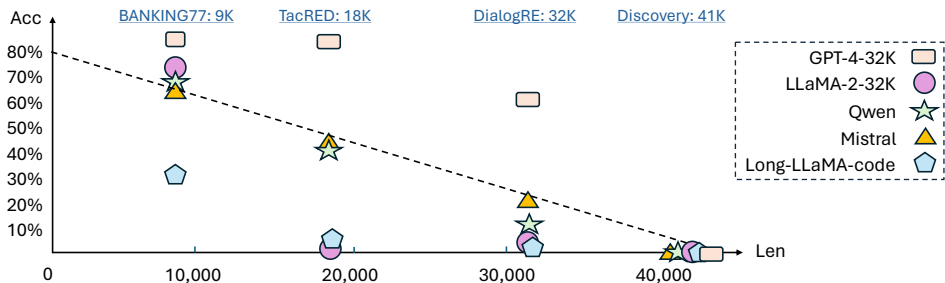
Figure 3: Results for representative models across different evaluation datasets. The performance greatly decreases as the task becomes more challenging. Some models even decays linearly w.r.t the demonstration length.

achieve high performance. Therefore, these metrics are insufficient to measure LLMs' ability to comprehend and reason over the entire input sequence.

In this paper, we propose to adopt in-context learning (ICL) on extreme-label classification tasks (Anil et al., 2022; Milios et al., 2023) to evaluate long-context LLMs. Unlike the prior tasks, in-context learning requires LLMs to recognize the task by scanning over the entire input to understand the label space. This task necessitates LLMs' ability to comprehend the entire input to make predictions. Due to the massive label space, the task demonstration could easily become a long sequence. For example, Discovery (Sileo et al., 2019) encompasses 174 classes with each example taking an average of 61 tokens. Therefore, the minimum demonstration for 1 shot/class already exceeds 10K tokens. Normally, LLMs demands more than 1 shot/class to understand the nuances of different fine-grained labels. Thus, this task becomes a natural testbed for long context understanding.

To systematically assess how these extended input capabilities affect model performance in the realm of fine-grained text classification with in-context learning, we have compiled a benchmark, i.e. *LongICLBench*, consisting of six carefully-selected tasks with different difficulty levels in terms of context length and label space.

We evaluate the performance of 13 long-context LLMs and **find that the performance of the models uniformly dips as the task becomes more complex (e.g. requiring longer demonstration) as shown in Figure 3. Some models like Qwen and Mistral even degrade linearly w.r.t. the input length. Simultaneously, most of the models can benefit from the extensive demonstration if the length is within a certain range. As the input grows longer, it either hurts or makes the performance fluctuate as shown in Figure 1**. Moreover, we make further analysis on the distribution of label position to investigate the factors that take effects on the long in-context learning capability of these models. **It is shown that the position distribution of instances in the prompt can dramatically influence the performance of some of the evaluated models including GPT4-turbo**.

In a nutshell, our contributions to this work can be summarized as follows:

- We have developed *LongICLBench*, dedicated to assessing long in-context learning tasks for large language models. This benchmark serves as a complement to earlier benchmarks that concentrated on tasks like long document summarization, question answering (QA), or retrieval, focusing instead on long in-context learning.
- We evaluate a line of recent long-context LLMs on *LongICLBench* and reveal their performances with gradually changed difficulty level. Simultaneously, we find the sensitivity of some of the long-context LLMs in regard to instance position in the prompt. We hope the evaluation results can provide more insights for the improvement of the design of long-context large language models.

2 Related Work

Long In-context Learning on LLMs As pre-trained language models continue to grow in size, in-context learning (ICL) has emerged as a favored approach for addressing a wide

array of tasks without the need for extensive fine-tuning (Dong et al., 2023). A body of research has established that increasing the number of example demonstrations can enhance ICL performance (Liu et al., 2022; Wu et al., 2023). Nonetheless, there are studies indicating that longer input prompts can actually diminish performance (Liu et al., 2023), with the effectiveness of prior large language models (LLMs) being constrained by the maximum sequence length encountered during their training. To counter this issue, various works have introduced memory augmentation and extrapolation techniques to support ICL with an extensive set of demonstrations (Li et al., 2023c; Wang et al., 2023).

Long Context Techniques over LLMs The effectiveness of Transformer-based models is hindered by the quadratic increase in computational cost relative to sequence length, particularly in handling long context inputs. Recent efforts have explored various strategies to address this challenge. Some studies have pursued continued fine-tuning of the LLM with longer context inputs, aiming to adapt the model to extended sequences (Rozière et al., 2024; Tworkowski et al., 2023). Others have leveraged techniques such as position extrapolation and interpolation, building upon relative rotary positional embedding (Su et al., 2021), to extend input length beyond the training phase (Press et al., 2022; Chen et al., 2023a). Additionally, a range of approaches has been proposed to mitigate computational issues, including sliding memory window and chunk segmentation methods (Hao et al., 2022; Ratner et al., 2023; Zhu et al., 2024). Furthermore, alternative architectures beyond the Transformer have been explored to handle long inputs more naturally, such as selective-state-spaces models, which represent a variation of recurrent neural networks Peng et al. (2023a); Gu & Dao (2023). These diverse approaches claim that they can enhance the capabilities of LLMs in processing long context inputs more efficiently.

Long Context Evaluation Due to the imperious demands for the support of long-range LLMs, there is a series of benchmarks focusing on long context evaluation. Long-Range Arena (Tay et al., 2021) includes tasks consisting of sequences ranging from 1K to 16K tokens to evaluate variations of fast Transformers. LongBench (Bai et al., 2023b) comprises 21 bilingual datasets within 6 types of tasks with an average length of around 6k words, which have been processed in a unified format to enable effortless evaluation. L-Eval Benchmark (An et al., 2023) supports 20 sub-tasks with input lengths of 3K to 200K tokens. LooGLE (Li et al., 2023b) focuses on summarization and four types of long dependency QA tasks with test instances exceeding 100k words. Most recently, ∞Bench (Zhang et al., 2024) encompasses 12 tasks, collecting from realistic, auto-generated, and human-annotated datasets with an average length of 200K tokens. Versatile as these benchmarks, none of them focus on exploring the capability of LLMs confronted with long in-context learning with extreme label space, which is quite different from the tasks of long-document understanding or synthetic needle in a haystack. Thus, our *LongICLBench* is proposed to fill the niche and make a more comprehensive long-context evaluation for LLMs.

Extreme-label Classification Extreme-label Classification involves categorizing data into one of an extremely large number of labels, and finds application across a variety of real-world domains such as emotion classification from text, named entity recognition, and biological function prediction, each requiring precise differentiation among vast label spaces (Zhang et al., 2017; Sileo et al., 2019; Demszky et al., 2020; Ding et al., 2021). Existing methods to tackle Extreme-label Classification tasks range from embedding-based approaches to fine-tuned retrievals (Bhatia et al., 2015; Vulić et al., 2021), focusing on efficiently managing and leveraging the large label space. However, integrating this task with long-context large language models presents unique challenges. The sheer scale of the label space in extreme-label classification complicates the in-context learning process, where LLMs are expected to discern fine-grained differences among labels based on extensive context (Milios et al., 2023). These challenges make the proposed *LongICLBench* with a range of difficulty level a good testing scenario to evaluate the capability of long-context large language models.

Dataset	Task Type	# Classes	# Tokens/Shot	# Total Tokens
GoEmotion	Emotion Classification	28	28	[1K, 4K]
BANKING77	Intent Classification	77	28	[2K, 11K]
TecRED	Relation Extraction	41	80	[4K, 18K]
Few-NERD	Entity Recognition	66	61	[5K, 23K]
DialogRE	Relation Extraction	36	226	[8K, 32K]
Discovery	Discourse Marker Classification	174	61	[10K, 50K]

Table 1: Statistics of the collected sub-dataset in *LongICLBench*. We evaluate from 1-shot/label to 5-shot/label, which results in the shown #total token range.

3 Long In-context Evaluation

3.1 Long In-context Benchmark

To support the evaluation of long in-context learning on extreme-label classification tasks in different domains and various difficulty levels, we collect six datasets containing context length from short to long. In order to balance the sequence token length within each dataset and the goal of evaluation for long in-context learning, we keep a subset of the classes among all the classes to format evaluation sets around 1 round, 2 rounds, 3 rounds, 4 rounds, and 5 rounds correspondingly, where each round represent a complete set of examples containing all unique chosen labels. We sample the number of instances from each of the classes evenly to reduce the bias resulting from the label distribution. The statistics of the datasets are described in detail in Table 1 and Appendix A.1.

BANKING77 (Casanueva et al., 2020) is a banking-domain intent detection dataset comprising 13,083 annotated examples over 77 intents. We keep all of the types of intents, and each of the instances contains around 28 tokens.

TacRED (Zhang et al., 2017) is a large-scale relation extraction dataset with 106,264 examples built over news and web text from the corpus used in the yearly TAC Knowledge Base Population. Only one relation is labeled for each of the sentences in the dataset. It covers 41 relation types in total, with an average length of 80 tokens for each example.

DialogRE (Yu et al., 2020) is a human-annotated dialogue-based relation extraction dataset composed of 1788 dialogues from a famous American television comedy, Friends, with 36 possible relation types existing between an argument pair in a dialogue. Each example contains around 226 tokens on average.

Discovery (Sileo et al., 2019) automatically discovers sentence pairs with relevant discourse markers and curates a large dataset containing 174 discourse markers with at least 10K examples each. Each example contains around 61 tokens. There are 174 types of discourse markers. This dataset is the most difficult task with fine-grained labels.

3.2 Model and Experimental Setup

In the exploration of in-context learning for extreme-label classification, we conduct a comprehensive evaluation for a series of recent open-source long-context language models of size around 7B parameters. We also include the SoTA models like Gemini and GPT-4-turbo. Table 2 provides an overview of the models investigated, highlighting the innovations in their architecture specifically for dealing with long context. We can observe that there are multiple strategies adopted to extend the context window. Some of the models support the training context window size while some models support length extrapolation. RWKV (Peng et al., 2023a) and Mamba (Gu & Dao, 2023) are the two new RNN-like architectures to decrease attention complexity, which would allow the model to easily extrapolate to much longer inputs with linear time/memory complexity.

We construct a prompt following the template as shown in A.2 for each of the datasets. To fairly evaluate the open-source and API-based models with a series of input lengths, we sample the same example set for all the models with labels distributed evenly to ensure

Model	Size	Initialization	Strategy	Train	Support
Gemma-7B-base	7B	Gemma	RoPE + LF	8K	8K
LLaMA-2-7B-32K	7B	LLaMA-2	Position Interpolation	32K	32K
ChatGLM3-6B-32K	6B	ChatGLM	Position Encoding Scheme	32K	32K
Qwen-1.5-7B-base	7B	Qwen	NTK-Aware Interpolation	32K	32K
Mistral-7B-v0.2-base	7B	Mistral	LF	32K	32K
LLaMA-2-7B-LongLora	7B	LLaMA-2	Shifted Short Attention	100K	100K
Yi-6B-200K	6B	Yi	Position Interpolation +LF	200K	200K
InternLM2-7B-base	7B	InternLM	Dynamic NTK	32K	200K
Long-LLaMA-code-7B	7B	LLaMA-2	Focused Transformer	8K	256K
RWKV-5-World	3B	RWKV	Attention-free Model	4K	∞
Mamba-2.8B	2.8B	Mamba	State Space Model	2K	∞
Gemini-1.0-Pro	-	Gemini	Ring Attention	32K	32K
GPT4-turbo	-	GPT-4	-	-	128K

Table 2: The overview of the evaluated models. We utilize base models before instruction-tuning except Gemini and GPT4-turbo. LF means fine-tuning the model on longer-context corpus after pre-training.

an unbiased distribution for the in-context demonstration. For instance, an input of one round will include one set of examples traversing all the types, and 5 rounds will contain instances from each of the labels for 5 times. For testing, we sample 500 examples from the test set of each dataset, simultaneously ensuring an even distribution in terms of the type of labels. All the open-source models are loaded from the weights in HuggingFace[1], while the API-based models are called with the scripts in the official documentations [2].

3.3 Experiment Result

The main evaluation results are demonstrated in Table 3, Table 4, Table 5 and Table 6. For the entity recognition and relationship extraction dataset, we use the F1 score as the evaluation metric, and Accuracy is utilized for the other datasets. From the presented results, generally, we can find that models of Transformer-based architecture perform consistently better than the RNN-based ones in all the evaluated datasets. However, both of them are still falling behind the powerful API-based models, especially GPT4-turbo. For a relatively simple task like BANKING77, whose context length from 1 round to 5 rounds is 2K to 14 K, most of the models can benefit from the extensive context with more demonstrations. As shown in Figure 1 and Table 3, from 2K to 4K, there is either a huge increase nearly doubling the accuracy, or a complete failure for most of the open-source models. After 3 rounds, limited performance gain can be achieved by adding more examples. When it comes to more complicated tasks like TacRED and DialogueRE in Table 4 and Table 5, which are more urgently requiring the capability of long-context comprehension, the overall performance of all the few-shot models drops compared to BANKING77. As shown in Figure 1, except GPT4-turbo can consistently benefit from more demonstrations, all of the other models reach their peak at the middle with context length around 20K.

For the most challenging Discovery dataset, which has an extremely large label space including 174 classes, one round of traversing for all the label possibilities has already made up a context length of 10K. In this extreme case, all of the models, including GPT4-turbo, fail to tell the difference among the fine-grained types, leading to a score of 0. The results across different datasets reveal the models' capability to understand different types of tasks. Our initial hypothesis suggests that the strongest LLMs like GPT-4-turbo are capped at a certain complexity level between DialogRE and Discovery.

Another interesting observation we have is that some LLMs' performance on the extreme-label ICL seems highly predictable. According to Figure 3, the performance of Qwen and

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[1] https://huggingface.co

[2] https://platform.openai.com/docs/guides/text-generation/chat-completions-api, https://cloud.google.com/vertex-ai/generative-ai/docs/multimodal/overview

Mistral are almost linear w.r.t the demonstration length. This reveals that there might be an underlying mathematical relation between performance and the task complexity for ICL.

Model	Param	Support	1R	2R	3R	4R	5R
Context Tokens			**2K**	**4K**	**7K**	**9K**	**14K**
Gemma-7B-base	7B	8K	0	0	0	0	0
LLaMA-2-7B-32K	7B	32K	**30.2**	**70.4**	**72.0**	**75.6**	**77.2**
ChatGLM3-6B-32K	6B	32K	16.6	23.2	22.4	22.8	8.8
Qwen-1.5-7B-base	7B	32K	21.6	52.8	61.4	66.0	67.8
Mistral-7B-v0.2-base	7B	32K	29.8	43.6	66.4	67.8	64.0
LLaMA-2-7B-LongLora	7B	100K	0	0	0	0	0
Yi-6B-200K	6B	200K	25.8	0	0	0	1.2
InternLM2-7B-base	7B	200K	5.6	0	0	0	0
Long-LLaMA-code-7B	7B	256K	3.0	19.4	28.0	31.6	32.6
RWKV-5-World	7B	4K	8.6	21.2	0.4	0	0
Mamba-2.8B	2.8B	2K	0	0	0	0	0
Gemini-1.0-Pro	N/A	32K	33.4	41.4	40.6	45.6	50.2
GPT4-turbo	N/A	128K	**73.5**	**80.5**	**82.0**	**83.5**	**84.4**
SoTA (RoBERTA + ICDA)	N/A	-			94.4		

Table 3: BANKING77 result with respect to increasing context length. **1R** represents one round of traversing all the instances with unique label.

Model	Param	Support	1R	2R	3R	4R	5R
Context Tokens			**4K**	**7K**	**10K**	**14K**	**18K**
Gemma-7B-base	7B	8K	0.4	0.4	0	0	0
LLaMA-2-7B-32K	7B	32K	0	0.4	0.4	0.8	0.4
ChatGLM3-6B-32K	6B	32K	29.7	36.1	38.9	40.1	25.2
Qwen-1.5-7B-base	7B	32K	38.7	47.3	45.2	43.6	40.6
Mistral-7B-v0.2-base	7B	32K	**53.3**	**53.1**	**51.6**	**48.0**	**42.3**
LLaMA-2-7B-LongLora	7B	100K	0	0	0	0	0
Yi-6B-200K	6B	200K	5.6	1.9	8.0	9.5	2.0
InternLM2-7B-base	7B	200K	29.6	27.2	15.5	10.7	8.0
Long-LLaMA-code-7B	7B	256K	3.8	7.1	4.1	6.6	4.9
RWKV-5-World	7B	1K	2.3	2.6	1.0	0	1.2
Mamba-2.8B	2.8B	2K	0	0	0	0	0
Gemini-1.0-Pro	N/A	32K	71.4	77.8	78.2	77.4	76.8
GPT4-turbo	N/A	128K	**74.4**	**76.5**	**79.5**	**80.4**	**84.2**
SoTA (DeepStruct)	N/A	-			76.8		

Table 4: TacRED result with respect to increasing context length.

4 Exploratory Experiment

Inspired by the Lost in the Middle phenomenon Liu et al. (2023), we take analysis experiments to explore whether the position distribution of the instances will make a difference in the performance for long in-context learning with extreme-label classification tasks.

4.1 Scattered Distribution

In our investigation, we conducte pilot experiments on TacRED, a medium-complexity dataset, with each label type demonstrated three times, resulting in a total of 123 distinct instances (calculated as 41×3). Within these experiments, instances bearing the same labels are distributed randomly to form a scattered configuration. For each instance, we track its relative position within the prompt alongside its corresponding label, thereafter computing the accuracy for each label class. As illustrated in the first row of Figure 4,

Model	Param	Support	1R	2R	3R	4R	5R
Context Tokens			**8K**	**13K**	**19K**	**25K**	**32K**
Gemma-7B-base	7B	8K	16.3	0	0	0	0
LLaMA-2-7B-32K	7B	32K	6.9	13.9	6.3	5.7	5.9
ChatGLM3-6B-32K	6B	32K	5.1	8.9	8.8	12.4	10.4
Qwen-1.5-7B-base	7B	32K	14.4	18.4	15.5	16.4	13.2
Mistral-7B-v0.2-base	7B	32K	**24.3**	**23.2**	**23.4**	**22.3**	**21.2**
LLaMA-2-7B-LongLora	7B	100K	0	0	0	0	0
Yi-6B-200K	6B	200K	0	0	0.8	0.8	0
InternLM2-7B-base	7B	200K	12.2	13.4	6.4	2.1	1.1
Long-LLaMA-code-7B	7B	256K	4.0	3.8	3.0	6.4	2.2
RWKV-5-World	7B	4K	0	0	0	0	0
Mamba-2.8B	2.8B	2K	0	0	0	0	0
Gemini-1.0-Pro	N/A	32K	23.6	29.2	33.2	26.1	17.3
GPT4-turbo	N/A	128K	**43.5**	**48.8**	**53.6**	**60.2**	**60.9**
SoTA (HiDialog)	N/A	-			**77.1**		

Table 5: DialogRE result with respect to increasing context length.

Model	Param	Support	1R	2R	3R	4R	5R
Context Tokens			**10K**	**20K**	**30K**	**40K**	**50K**
Gemma-7B-base	7B	8K	0	0	0	0	0
LLaMA-2-7B-32K	7B	32K	0	0	0	0	✗
ChatGLM3-6B-32K	6B	32k	0	1.0	0	✗	✗
Qwen-1.5-7B-base	7B	32K	0	0	0	0	0
Mistral-7B-v0.2-base	7B	32K	0	0	0	0	0
LLaMA-2-7B-LongLora	7B	100K	0	0	0	0	0
Yi-6B-200K	6B	200k	0	0	0	0	0
InternLM2-7B-base	7B	200K	0	0	0	0	0
Long-LLaMA-code-7B	7B	256K	0	0	0	0	0
RWKV-5-World	7B	4K	0	0.2	0	0	0
Mamba-2.8B	2.8B	2K	0	0	0	0	0
Gemini-1.0-Pro	N/A	32K	0	0	0	✗	✗
GPT4-turbo	N/A	128K	**1.5**	**0.5**	**0.5**	**0.5**	**0.5**
SoTA (MTL)	N/A	-			**87.4**		

Table 6: Discovery result with respect to increasing context length.

the visualization delineates the accuracy of each label, aligned with its position within the prompt, where diverse colors symbolize various label types. In scenarios where class instances are scattered, certain models, such as InternLM2-7B-base, demonstrate acceptable performances—approximately 60% accuracy merely on specific labels, as highlighted by a red circle in Figure 4, regardless of the instance placements. Conversely, other models, like ChatGLM3-6B-32K, exhibit robust performance across a broad spectrum of labels. Remarkably, the GPT4-turbo model consistently surpasses an 80% accuracy threshold for the majority of label types, with only a minimal count of exceptions.

4.2 Grouped Distribution

To facilitate a clear comparison between scattered and grouped distributions, we organize instances of the same class to be adjacent within the demonstration prompts. The impact of this reorganization on model performance, both pre and post-grouping, is presented in Table 7. A pronounced trend emerges, highlighting a general decline in performance across most models after grouping instances by class. Notably, models such as Mistral-7B-v0.2-base and InternLM2-7B-base exhibit significant performance drops, underscoring a pronounced sensitivity to instance grouping. In an effort to delve deeper into this phenomenon, we
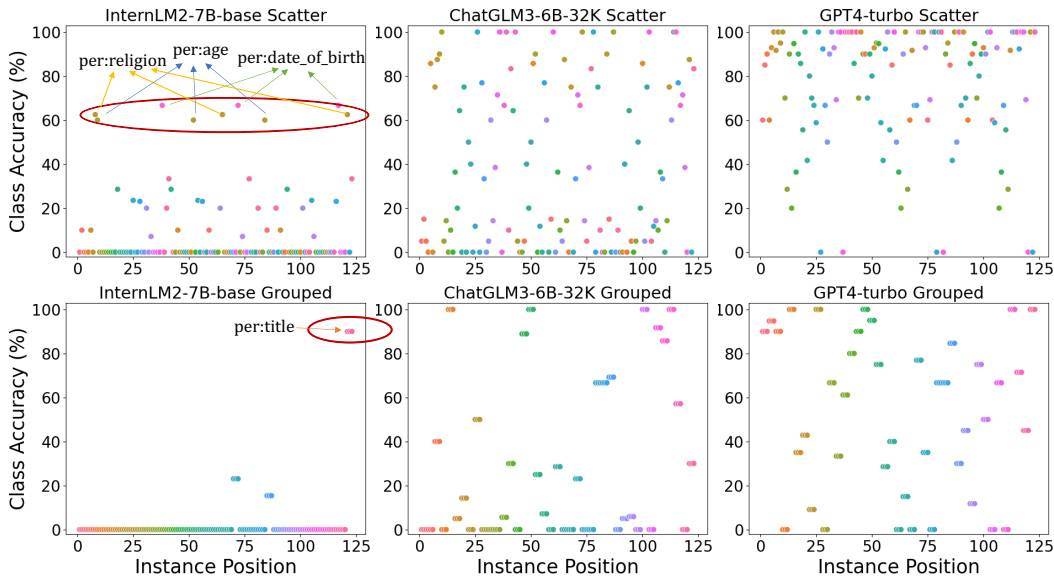
Figure 4: Visualization of accuracy for every class when instances from the same class are scattered V.S. grouped in the demonstration prompt.

visualize the accuracy of grouped labels in relation to their positions within the prompt, as illustrated in Figure 4. This visualization reveals that instances of the same class, denoted by dots of the same color, are positioned in close proximity. It became evident that some models, like InternLM2-7B-base, demonstrate high sensitivity to the distribution of instances, only handling instances with labels positioned at the end of the prompt. Conversely, other open-source models such as ChatGLM3-6B-32K, with a modest 3.3% drop in accuracy, proved to be more resilient to changes in instance positioning, maintaining high performance across varied positions. Surprisingly, even the GPT4-turbo is not immune to the challenges posed by grouped distributions, experiencing a notable decline in performance by 20.3%. This observed decrease in performance is consistent across models, unaffected by the specific positions of the labels within the prompt.

Model	Param	Support	Scatter	Grouped	Δ
Context Tokens				10K	
Gemma-7B-base	7B	8K	0	0	0
LLaMA-2-7B-32K	7B	32K	0.4	3.0	+2.6
ChatGLM3-6B-32K	6B	32K	38.9	35.6	-3.3
Qwen-1.5-7B-base	7B	32K	45.2	33.0	-12.2
Mistral-7B-v0.2-base	7B	32K	51.6	5.1	-46.5
LLaMA-2-7B-LongLora	7B	100K	0	0	0
Yi-6B-200K	6B	200K	8.0	0	-8
InternLM2-7B-base	7B	200K	15.5	4.8	-9.7
Long-LLaMA-code-7B	7B	256K	4.1	0	-4.1
RWKV-5-World	7B	4K	1.0	3.6	+2.6
Mamba-2.8B	2.8B	2K	0	0	0
GPT4-turbo	N/A	128K	79.5	59.2	-20.3

Table 7: Exploratory Result on TacRED 3 Round. **Grouped** means forcing the same-typed demonstration examples near by each other instead of randomly distributing in the prompt.

5 Conclusion

In summary, our research explores the capability of large language models on long in-context learning tasks, particularly in extreme-label classification scenarios. We curate a dataset *LongICLBench* consisting of long in-context learning tasks with different difficulty level in respect to the context length. Through our study, we have discovered that while LLMs show promising performance on inputs up to 20K tokens, their ability to process and understand longer sequences significantly decreases. Our exploratory experiments further highlight the impact of the distribution of examples within prompts on model performance. We hope *LongICLBench* and our findings contribute to the ongoing efforts to enhance LLMs' understanding of long contexts.

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A   Appendix

A.1   Additional Datasets

We list a few additional datasets as follows:

GoEmotions (Demszky et al., 2020) is the largest manually annotated dataset of 58k English comments from Reddit, which is labeled into 27 emotion categories or Neutral. There are 27 types of emotion types and drop the rare ones with few examples. Each selected example contains 28 tokens on average.

Few-NERD (Ding et al., 2021) is a large-scale human-annotated name entity recognition dataset with a hierarchy of 8 coarse-grained and 66 fine-grained entity types. Each of the instances is a paragraph with approximately 61 tokens on average and contains one or multiple entity names as the ground truth answer. There are 66 types of entities in the collection.

The performance for the two tasks is demonstrated in Table 8 and Table 9.

Model	Param	Support	1R	2R	3R	4R	5R
Context Tokens			**0.8K**	**1.6K**	**2.4K**	**3.2K**	**4K**
Gemma-7B-base	7B	8K	0	0	0	0	0
LLaMA-2-7B-32K	7B	32K	0	0	0	0.2	0.2
ChatGLM3-6B-32K	6B	32K	**22.0**	17.0	15.0	12.6	10.6
Qwen-1.5-7B-base	7B	32K	14.8	**18.2**	**18.6**	**19.0**	**14.2**
Mistral-7B-v0.2-base	7B	32K	2.6	11.4	7.4	11.6	12.4
LLaMA-2-7B-LongLora	7B	100K	0	0	0	0	0
Yi-6B-200K	6B	200K	0	0	0.8	4.0	4.0
InternLM2-7B-base	7B	200K	0	0	0	0	0
Long-LLaMA-code-7B	7B	256K	0	0	0	0.2	0.4
RWKV-5-World	7B	4K	8.8	7.4	4.6	5.2	4.0
Mamba-2.8B	2.8B	2K	0	0	0	0	0
Gemini-1.0-Pro	N/A	32K	20.3	21.4	22.4	24.4	24.0
GPT4-turbo	N/A	128K	**36.5**	**34.4**	**35.0**	**33.3**	**32.0**
SoTA (BERT)	N/A	-			58.9		

Table 8: GoEmotion Result.

Model	Param	Support	1R	2R	3R	4R	5R
Context Tokens			**5K**	**9K**	**14K**	**19K**	**24K**
Gemma-7B-base	7B	8k	**44.0**	44.2	0	0	0
LLaMA-2-7B-32K	7B	32k	36.9	40.8	41.1	41.6	41.3
ChatGLM3-6B-32K	6B	32k	24.1	9.3	23.6	10.4	1.1
Qwen-1.5-7B-base	7B	32k	40.0	46.4	47.6	47.3	47.8
Mistral-7B-v0.2-base	7B	32K	42.2	**47.4**	**48.9**	**50.0**	**50.0**
LLaMA-2-7B-LongLora	7B	100K	0	0	0	0	0
Yi-6B-200K	6B	200k	34.3	40.2	44.8	42.3	43.2
InternLM2-7B-base	7B	200k	43.6	46.2	46.5	47.8	48.3
Long-LLaMA-code-7B	7B	256K	22.3	25.5	26.5	29.4	27.0
RWKV-5-World	7B	1k	13.9	0	0	0.7	9.9
Mamba-2.8B	2.8B	2k	0	0	0	0	0
Gemini-1.0-Pro	N/A	32k	36.8	26.1	28.5	27.4	28.4
GPT4-turbo	N/A	128k	**53.4**	**55.3**	**56.2**	**55.6**	**56.8**
SoTA (PL-Marker)	N/A	-			70.9		

Table 9: Few-NERD Result.

A.2 Prompting Template

Dataset	Prompt
GoEmotion	Given a comment, please predict the emotion category of this comment. The prediction answer must come from the demonstration examples with the exact format. The examples are as follows: {comment: "...comment..." emotion category: "...emotion..." } × *repeat n times*
BANKING77	Given a customer service query, please predict the intent of the query. The predicted answer must come from the demonstration examples with the exact format. The examples are as follows: {service query: "...service..." intent category: "...intent..." } × *repeat n times*
TecRED	Given a sentence and a pair of subject and object entities within the sentence, please predict the relation between the given entities. The examples are as follows: {sentence: "...sentence... the subject is "...subject..." the object is "...object..." the relation between the two entities is: "...relation..." } × *repeat n times*
Few-NERD	Given the sentence, please find the name entities in the sentence and their corresponding entity types in the strict format of the given examples as following (Entity: EntityType): {"...entity...": "...entity type..." } × *repeat n times*
DialogRE	Given the dialogue, please find the name pair entities in the dialogue and their corresponding relation types in the strict format of given examples as following (note that the number of entities has to strictly have the same value as the number of respective relation): {Dialogue: "...dialogue..." The list of entity pairs are "...(subject1, object1), (subject2, object2), etc... The "...number of pairs..." respective relations between each entity pair are: "...relation, relation2, etc... } × *repeat n times*
Discovery	Given two sentence1 and sentence2, please predict the conjunction word between the two sentences. The predicted answer must come from the demonstration examples with the exact format. The examples are as follows: {"...sentence1..." ( ) "...sentence2..." the conjunction word in ( ) is "...conjunction..." } × *repeat n times*

Table 10: The data prompt format of each dataset. Each dataset has a unique prompt format to effectively utilize the context and format of its respective data to get the best output response.

The prompting template for each of the dataset is presented at Table 10