# LLM Maybe LongLM: Self-Extend LLM Context Window Without Tuning

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### Abstract

This work elicits LLMs' inherent ability to handle long contexts without fine-tuning. The limited length of the training sequence during training may limit the application of Large Language Models (LLMs) on long input sequences for inference. In this work, we argue that existing LLMs themselves have inherent capabilities for handling long contexts. Based on this argument, we suggest extending LLMs' context window by themselves to fully utilize the inherent ability.We propose Self-Extend to stimulate LLMs' long context handling potential. The basic idea is to construct bi-level attention information: the group level and the neighbor level. The two levels are computed by the original model's self-attention, which means the proposed does not require any training. With only four lines of code modification, the proposed method can effortlessly extend existing LLMs' context window without any fine-tuning. We conduct comprehensive experiments and the results show that the proposed method can effectively extend existing LLMs' context window's length.

# 1. Introduction

The context window length of most existing LLMs is limited since they are trained with a fixed length of training sequences. It's determined by the context window length during the pretraining stage. Once the length of the input texts exceeds the pretraining context window during the inference, the behavior of LLMs will be unpredictable and suffer from severe performance degradation, which is shown on the perplexity (PPL) metric, the PPL of the model will explode with the long input sequence (Xiao et al., 2023; Peng et al., 2023b; Han et al., 2023; Chen et al., 2023b). have been developed to tackle the challenge of extending the context window size of pretrained LLMs. A common and straightforward approach is to fine-tune these models on enough extensive texts (Xiong et al., 2023). Besides this, some methods seek to achieve extension either without the need for fine-tuning or with only minimal fine-tuning, offering a more efficient alternative. Among these contemporary methods, some notable techniques include 'PI' (Chen et al., 2023b), 'CLEX' (Chen et al., 2023a) and 'Yarn' (Peng et al., 2023b). However, they typically necessitate a few finetuning steps to achieve extension, which could be resourceintensive and time-consuming. And these methods aim to extend the content window based on the assumption that pretrained LLMs lack the ability to handle long content. Thus, limited finetuning could make LLMs overfit to specific long sequences, which lacks generalizability over out-ofdistribution long sequences and loses performance on short sequences obtained during pretraining. On the other hand, some methods (Xiao et al., 2023; Han et al., 2023; Ding et al., 2023) aim to avoid fine-tuning. These fine-tuningfree approaches rely predominantly on local information in the sequence. However, these methods may fall short in effectively expanding the context window, as it is limited to using only local tokens rather than expanding the overall context-handling capacity of the LLMs. Consequently, they may not fully realize the potential of extending the context window in LLMs and have inferior performance.

Recently, a variety of content window extension methods

Instead of extending the content window, in this paper, we believe **LLMs should have inherent capabilities to handle long contexts**. Our belief stems from the fact that when we, as human beings, are children, we are taught how to read and write using relatively short texts, such as articles spanning several pages. We rarely use extremely long texts like entire books or complete documents as learning materials. Yet, we are still able to understand long texts effectively. With this strong motivation, the poor performance of LLMs while facing long text out of the pretraining context window size is not due to the lack of long context understanding capabilities. We suppose that there should be a way to elicit LLMs' inherent long context capability.

In our analysis, we observe that the key challenge preventing LLMs from effectively managing extensive contexts is

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the out-of-distribution (O.O.D) issues related to positional encoding, which we call the *positional*  $O.O.D^1$  issue. This problem arises when LLMs encounter text sequences during inference exceeding the length of their pretraining context window, where LLMs are exposed to new relative distances that were not present during their pretraining phase. It is widely recognized that neural networks (NNs) are susceptible to unpredictable behaviors when dealing with O.O.D inputs. To address this, an intuitive and practical solution would be to remap the unseen relative positions to those encountered during the pretraining, thus extending the LLMs' ability to handle longer contexts naturally.

We propose Self-Extend to elicit LLMs' inherent long context capabilities. To overcome the positional O.O.D issue, Self-Extend uses the simple FLOOR (//) operation as the mapping function to map unseen large relative positions to those encountered during pretraining. This idea stems from two intuitions: 1) For texts with a long distance between words, the exact position does not need to be precise. It is sufficient to understand the overall meaning of the text as long as the relative ordering of the different parts is maintained. When answering a question about information from a lengthy text, we never remember the precise position of each word, just the general position and order of the relevant information. Since natural language texts tend to have similar semantics within a short range (e.g. a paragraph), close or even equal position encodings should be adequate for maintaining the relative ordering of useful information. This aligns with the floor operation. 2) In natural language texts, most of the time, while a small bag of words (ngrams) appears together in one area, all the tokens in that bag have only one possible order due to the conventions of the language grammar. Although theoretically, a bag of tokens could appear in any order, in practice it is rare for a small set of words to have more than one sensible ordering. For example, "unnecessary encodings" can be tokenized as "unn", "ecessary", " enc" and "odings"<sup>2</sup>, but these tokens can only meaningfully appear in that order. This suggests that maintaining precise position information is unnecessary in a small region, which also aligns with the floor operation.

Self-Extend is a plug-and-play method that takes effect at the inference stage, allowing existing large language models to easily adopt it. We evaluate Self-Extend with three popular LLMs (Llama-2, Mistral, and SOLAR) on three types of tasks: language modeling, synthetic long context tasks, and real-world long context tasks. The proposed Self-Extend substantially improves the long context understanding ability and even outperforms fine-tuning-based methods on some tasks. These results underscore Self-Extend as an effective solution for context window extension. The superior performance of SelfExtend also demonstrated the potential of large language models to effectively handle long contexts.

Our main contributions are summarized as follows:

- 1. We think LLMs with RoPE have a natural ability to handle long texts, even if they haven't encountered superlong ones during training. The previous limitation stems from out-of-distribution positions, meaning the "larger" positions haven't been seen during training. We call this the *positional O.O.D.* issue.
- Based on this belief and to address the positional O.O.D. issue, we propose SelfExtend to extend the context window of LLMs without any fine-tuning. Our proposal maps the unseen large relative positions (at inference) to known positions (at training), thus it allows LLMs to maintain coherence over longer texts without additional fine-tuning.
- 3. On both synthetic and real-world long context tasks, SelfExtend can achieve comparable or surprisingly better performance than many existing fine-tuning-based models.

### 2. Preliminary

In this section, we present the preliminaries of our work.

### 2.1. Position Encoding

Transformers (Vaswani et al., 2017) incorporate position information via different positional embedding designs. The common positional embedding design can generally be categorized into two classes: absolute position embeddings and relative positional encodings. The *absolute position embedding* provides the absolute positions, which embeds each absolute position *i* into position vector  $\mathbf{p}_i$  and adds word embeddings to their corresponding  $\mathbf{p}_i$  before feeding them to the model. Examples of such include sinusoidal position embeddings in GPT3 (Brown et al., 2017), and learned position et al., 2022), or adding the dot product between two tokens' position embeddings on the attention logit (Ke et al., 2020).

Recently, relative positional encodings have been proposed to instead use distance information between tokens and have become the mainstream of position embedding. This information is usually applied in attention layers. Examples of such include a learnable attention logit bias as in

<sup>&</sup>lt;sup>1</sup>Here, the position refers to relative position rather than absolute position. The relative position is m - n in RoPE, where m and n are the absolute positions of two tokens. The *positional* O.O.D refers to cases where the value of m - n during inference is unseen, i.e., larger than the values observed during pretraining. In this paper, we map unseen large relative positions to those observed during pretraining. More details about m - n are provided in Section 2.2.

<sup>&</sup>lt;sup>2</sup>The tokenization result is from OpenAI's tokenization tool.

T5 (Xue et al., 2020), Transformer-XL (Dai et al., 2019); a fixed linear attention decay called Alibi (Press et al., 2021); rotating query and key sequences based on distance such as RoPE (Su et al., 2023), and XPos (Press et al., 2021). The proposed method in this work is based on the Rotary Position Embedding (RoPE) introduced in (Su et al., 2022).

#### 2.2. RoPE

Previous works (Peng et al., 2023a; Longpre et al., 2023; Gupta et al., 2022) show that RoPE (Su et al., 2023) can effectively extend context windows to manage longer text sequences during inference. This section introduces the basic concept of RoPE. Let's consider a sequence of tokens represented as  $w_1, w_2, \dots, w_L$ , and their corresponding embeddings are denoted as  $\mathbf{x}_1, \dots, \mathbf{x}_L \in \mathbb{R}^{|D|}$ , where |D|is the dimension of the embedding.

The basic idea of RoPE is to incorporate the positional information into the query and the key vectors,  $\mathbf{q}$  and  $\mathbf{k}$  respectively. This integration ensures that their inner product  $\mathbf{q}^T \mathbf{k}$ will contain the relative positional embedding information inherently. To achieve this, RoPE employs the following vector transformations:

$$\mathbf{q}_m = f_q(\mathbf{x}_m, m) \in \mathbb{R}^{|L|}, \ \mathbf{k}_n = f_k(\mathbf{x}_n, n) \in \mathbb{R}^{|L|}, \quad (1)$$

where |L| is the hidden dimension of per head. The functions  $f_q$ ,  $f_k$ , responsible for injecting positional information, are defined as follows:

$$f_q(\mathbf{x}_m, m) = W_q \mathbf{x}_m e^{im\theta}, \ f_k(\mathbf{x}_n, n) = W_k \mathbf{x}_n e^{in\theta}, \ (2)$$

where  $\theta_d = b^{-2d/|D|}$ , b = 10000 and  $W_q, W_k : \mathbb{R}^{|D|} \to \mathbb{R}^{|L|}$ . RoPE keeps the real part of the inner product  $\mathbf{q}^T \mathbf{k}$ , which is  $\operatorname{Re}(\mathbf{q}^*\mathbf{k})$ . This operation ensures that the dot product of the query and key vectors depends entirely on the relative distance between the tokens, represented by m - n of the tokens as follows

$$\langle f_q(\mathbf{x}_m, m), f_k(\mathbf{x}_n, n) \rangle_{\mathbb{R}}$$
 (3)

$$= \operatorname{Re}(\langle f_q(\mathbf{x}_m, m), f_k(\mathbf{x}_n, n) \rangle_{\mathbb{C}})$$
(4)

$$= \operatorname{Re}(\mathbf{x}_{m}^{*}W_{q}^{*}W_{k}\mathbf{x}_{n}e^{i\theta(m-n)})$$
(5)

$$=g(\mathbf{x}_m,\mathbf{x}_n,m-n).$$
 (6)

The follow-up studies (Rozière et al., 2023; Peng et al., 2023b) demonstrate that RoPE can adapt to longer sequence lengths when pre-trained on shorter ones with fine-tuning. We believe LLMs with RoPE have an intrinsic ability to directly process long contexts, and this work focuses on harnessing this latent capability without the need for fine-tuning.

### 3. Our Proposal: Self-Extend Context Window

In this section, we first conduct a preliminary investigation on the inherent ability of the LLMs to handle long content.



Figure 1. On the left figure, we show the O.O.D. issue while the input length is out of the pretraining context window size. We suppose that the LLM's pretraining context window length is 5 and an input sequence with a length of 8 is put. The y-axis of this matrix represents the position of query tokens and the x-axis represents the position of key tokens. In this case, in the relative position matrix, only those in orange are valid and are seen during pretraining. Relative positions in gray are out of the pretraining context window and O.O.D. On the right figure, we show how the FLOOR operation is applied and the relative positions of query tokens and key tokens are mapped from 0-7 to 0-3 by FLOOR (//). The new relative positions (in blue) are all within the scope of the pretraining context window.

#### 3.1. Preliminary Analysis

① Why do LLMs fail on input out of the pretraining context window? We argue that such failure stems from the out-of-distribution issue of relative distance. Neural networks are not robust to out-of-distribution (O.O.D.) inputs (Shen et al., 2021). For a pretrained LLM with relative position encodings such as RoPE, at inference, if a sequence is longer than its pretraining context window length, the behavior of LLMs will be unpredictable. This has been elaborated by (Han et al., 2023; Chen et al., 2023b) that with unseen relative positions, the attention distributions are very different compared to those within the pretraining context window length.

<sup>(2)</sup> How can we bypass the length limitation while maintaining long-distance information? — Conduct group attention with the FLOOR operation. Our primary goal is to elicit LLMs' inherent capabilities without any fine-tuning. One feasible way to avoid the O.O.D. problems caused by unseen relative positions is to map new relative positions into those seen during pretraining. The FLOOR operation is a good fit for these requirements due to the following two folds:

- It can maintain the order information among tokens. Although, the orders between tokens with FLOOR mapping are not that precise.
- The FLOOR operation is simple and easy to implement.

In Figure 1, we show how the FLOOR operation is applied to map positions into positions within the pretraining context



*Figure 2.* Perplexity (PPL) of Llama-2-7b-chat using grouped attention on PG19 with different group size. The red dotted line indicates the PPL of the original Llama-2-7b-chat on 4k sequence. The purple dotted line indicates the PPL of the original Llama-2-7b-chat on 6k sequence and it explodes.

window. Everything is the same as the original self-attention mechanism except that before the inner product, the FLOOR operation is applied to each token's original position. In Python style, this operation can be denoted as "

$$P_q = P//G_s \tag{7}$$

while  $P \in \mathbb{R}^{B \times L}$  is the original position in integer. *B* is the batch size and *N* is the input text sequence length. *G<sub>s</sub>* is a hyperparameter of group size. It is the base of the FLOOR operation. We denote the self-attention with this FLOOR operations applied as 'grouped attention'.

3 Can LLMs work well without accurate position infor**mation?** — Yes, but not that perfect. In Figure 2, we show the perplexity (PPL) on the PG-19 (Rae et al., 2019) dataset with the FLOOR operation applied to several LLMs across different sequence lengths. As a comparison, we also show the PPL of original models without the FLOOR operation as the dotted lines. From this figure, with the FLOOR operation, LLMs can still keep a relatively good PPL. Meanwhile, with small group size, the PPL is a little higher than the original LLMs. This language modeling performance degradation is expected. However, it can imply the effectiveness of group attention and support our assumption about the coarse position encoding. The PPL is not too large and the LLMs' behavior w.r.t. PPL is similar to the original model that the PPL is nearly unchanged within the "context window" (for Llama-2: 2 - 8192, 4 - 16384, and 8 - 32768).

(1) How to reconstruct degraded language modeling ability caused by the group attention? — Re-introducing normal attention in the neighbor area. While generating a certain token, the neighbor tokens are the most important tokens to this token. This has been supported by many existing works from sparse attention (Zaheer et al., 2020; Shi et al., 2021) and context window extension (Han et al., 2023; Xiong et al., 2023; Chen et al., 2023c). All these

works keep the attention mechanism unchanged for neighbor tokens. This also aligns with the intuition: neighbor tokens are directly responsible for the generated next token. Once the neighbor tokens are precisely modeled by LLMs, at least, the generated sentence is fluent and the PPL should not be large. More specifically, if we use the previously mentioned grouped attention, although it will merely influence the understanding of the texts while generating the next token to construct a readable sentence, the precise position still needs to be provided. To conclude, we still need to keep the attention mechanism unchanged in the neighbor area, which would be the normal attention used in the pretraining stage.

### 3.2. Self-Extend LLM Context Window Without Tuning

With the aforementioned insights, we propose our method: Self-Extend, which contains two kinds of attention: the grouped attention is designed for tokens with long distance and it applies the FLOOR operation to the positions; the normal attention is for neighbor tokens within a certain range and there's no modification to this part. The diagram of Self-Extend is shown in Figure 3. Self-Extend only modifies the attention mechanism during inference and it does not require any fine-tuning or training.

Denote the pretraining context window size as L, the group size for grouped attention as G, and the window size for neighbor tokens as  $w_n$ . We shift the relative position of grouped attention by  $w_n - w_n//G$  before merging the two pieces of attention together. This is because that the transition from the normal attention area to the grouped attention area is smooth. We merge the two parts of attention by replacing the attention values out of the neighbor token window with the attention values from the grouped attention.

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Figure 3. This figure shows the attention score matrix (the matrix before SoftMax operation) of the proposed Self-Extend while a sequence of length 10 is input to a LLM with pretraining context window (L) of length 7. The number is the relative distance between the corresponding query and key tokens. Self-Extend has two kinds of attention mechanism: for neighbor tokens within the neighbor window  $(w_n, in this figure, it's 4)$ , it adapts the normal self-attention in transformers; for tokens out of the window, it adapts the values from the grouped attention. The group size (G) is set to 2. After the two parts merge, the same as the normal attention, the softmax operation is applied to the attention value matrix and gets the attention weight matrix.

All the modifications are applied before the softmax operation and other parts remain unchanged. The maximum length of the extended context window is:

$$(L - w_n) * G + w_n \tag{8}$$

For example, in Figure 3, the context window is extended from its pretraining length of 7 to (7 - 4) \* 2 + 4 = 10.

The python style pseudo codes for SelfExtend are presented in Algorithm 1.

# 4. Experiments

We evaluate the proposed Self-Extend primarily using the Llama-2 (Touvron et al., 2023) families considering its wide adoption and popularity. We also construct some experiments for other RoPE based models including the currently popular model Mistral (Jiang et al., 2023) and SOLAR (Kim et al., 2023), which received attention in recent days and it can show the advantage of quick adaption for Self-Extend.

The effectiveness of Self-Extend is evaluated on three kinds of tasks: language modeling, synthetic long context tasks and real long context tasks. Considering that most tasks have short contexts, we also construct an evaluation on standard short-context tasks.

#### 4.1. Performance on language modeling

Language modeling is the most fundamental and the least requirement to a LLM. A low PPL does not guarantee good performance on real tasks while a too high PPL suggests severe performance degradation of LLMs.

We evaluate Self-Extend's language modeling performance on PG19 (Rae et al., 2019), which contains long books. We use the first sentence of each book in PG19's test set (100 books) to test the language modeling ability. Perplexity (PPL) is used as the metric<sup>3</sup>. All PPL results were calculated using the sliding window method (Press et al., 2021) with S = 256. We evaluated how the PPL changes as the input length increases. In Table 1, Self-Extend extends the original Llama-2's context window length from 4096 (4k) to larger than 16384 (16k) with group size G set as 8 and neighbor window  $w_n$  set as 1024 (1k). For Mistral, without SWA, the context window is 8192 (8k) and it's also extended by Self-Extend with the same setting to larger than 16k. With SWA, Mistral can digest infinite length of sequences.

Self-Extend can successfully maintain a low PPL out of the pretraining context window for both Llama-2-chat and Mistral. Without Self-Extend, the PPL exploded out of the context window. Mistral with SWA can also maintain a low PPL out of its context window. But later in the next section, we will show the low PPL does not mean a true ability to handle long contexts.

### 4.2. Performance on synthetic long context tasks

The passkey retrieval task is as defined in (Mohtashami & Jaggi, 2023). It requires a language model to retrieve a simple passkey (a five-digit random number) in a long meaningless text sequence. This task is super simple, and it tests whether an LLM can be aware of the information across all positions of the input sequence.

Inspired by the design of "Needle in a Haystack" test (gkam-

<sup>&</sup>lt;sup>3</sup>This is not the standard setting for PPL testing on PG-19. The results cannot be directly compared to the PPL reported by other papers. We chose this setting because our computation resources are very limited. This setting saves a lot and it can still show the trend of PPL.

Model							
Name	4096	6144	8192	10240	12288	14336	16384
Llama-2-7b-chat SelfExtend-Llama-2-7b-chat	9.181 8.885	$> 10^{3}$ 8.828	$> 10^{3}$ 9.220	$> 10^{3}$ 8.956	$> 10^{3}$ 9.217	$> 10^{3}$ 9.413	$> 10^{3}$ 9.274
Mistral-7b-instruct-0.1 w/ SWA	9.295	9.197	9.532	9.242	9.198	9.278	9.294
Mistral-7b-instruct-0.1 w/o SWA SelfExtend-Mistral-7b-instruct-0.1	9.295 9.272	9.205 9.103	10.20 9.369	55.35 9.070	$> 10^{3}$ 8.956	$> 10^{3}$ 9.022	$> 10^{3}$ 9.128

*Table 1.* Perplexity on PG19 of Llama-2-7b-chat and Mistral-7b-instruct-0.1. Mistral has a unique sliding window attention (SWA) mechanism at inference. We show the PPL of with&without SWA for Mistral.

Table 2. Performance comparison of different models on LongBench. \* indicates the results reported by LongBench. \*indicates the results are reported by CLEX (Chen et al., 2023a). + indicates the result is from us. Models in green are based on Llama2-7b, models in blue are based on Mistral-7b, and models in orange are based on SOLAR-10.5B. The number (e.g. '25k') indicates the maximum input length. For each base model, the best performance is in **bold** and the second best performance is <u>underlined</u>. The 'SEext' prefix indicates Self-Extend is applied to this model. In this table, except Self-Extend, all other models require fine-tuning to extend the context window. CLEX is fine-tuned with 2B tokens. LongChat1.5-7B-32k and Vicuna1.5-7B-16K are fine-tuned on more than 80k conversations. CodeLLaMA (Rozière et al., 2023) is fine-tuned on more than 500B tokens. MistralLite (Yin Song and Chen Wu and Eden Duthie, 2023) is also fine-tuned on more than 2B tokens (amazon, 2023).

Madal	Sing	le-Docume	nt QA	Mul	ti-Document	QA	S	ummarizat	ion	Fe	w-shot Le	arning	Synth	netic		Code
Model	NarrativeQA	A Qasper 1	AultiField-e	1 HotpotQA	2WikiMQA	Musique	GovRepor	t QMSum	MultiNew	s TREC	TriviaQA	SAMSun	n PaasgeCount	PassageRe	Lcc	RepoBench-P
GPT-3.5-Turbo-16k*	23.6	43.3	52.3	51.6	37.7	26.9	29.5	23.4	26.7	68.0	91.4	41.7	4.5	71.0	54.7	53.6
XGen-7B-8k*	18	18.1	37.7	29.7	21.1	10.3	27.3	20.5	26.2	65.5	77.8	25.3	2.1	8.5	38.6	38.6
InternLM-7B-8k*	12.1	16.7	23.4	28.7	22.8	9.0	9.7	15.9	22.8	52.0	77.8	21.2	3.0	6.0	44.1	28.8
ChatGLM2-6B-32k*	21.1	31.5	46.2	45.1	34.0	21.9	32.4	24.0	26.5	62.5	78.7	36.3	1.5	77.0	55.6	49.9
ChatGLM3-6B-32k*	26.0	43.3	51.7	54.4	44.9	40.4	36.8	23.9	27.9	79.0	87.1	38.2	2.0	99.0	57.66	54.76
Baichuan-13B-4k*	0.07	17.55	17.28	3.29	15	0.1	6.8	1.71	23.1	20.05	20.06	5.77	0.06	0.5	47.98	16.58
ALiBi-7B-4k*	0.04	8.13	17.87	2.73	8	1.33	5.31	1.64	25.55	9.25	8.83	4.67	0	1.27	46.69	18.54
Llama2-7B-chat-4k*	18.7	19.2	36.8	25.4	32.8	9.4	27.3	20.8	25.8	61.5	77.8	40.7	2.1	9.8	52.4	43.8
LongChat1.5-7B-32k*	16.9	27.7	41.4	31.5	20.6	9.7	<u>30.8</u>	22.7	26.4	63.5	82.3	34.2	1.0	30.5	53.0	55.3
CLEX-7B-16k	18.05	23.68	44.62	28.44	19.53	9.15	32.52	<u>22.9</u>	25.55	68	84.92	42.82	0	11.5	59.01	56.87
CodeLLaMA-7B-16k*	22.93	30.69	<u>43.37</u>	33.05	27.93	<u>14.2</u>	28.43	24.18	26.84	70	84.97	43.43	2	<u>13.5</u>	64.35	<u>55.87</u>
SEext-Llama-2-7B-chat-16k+	21.69	25.02	35.21	<u>34.34</u>	30.24	14.13	27.32	21.35	25.78	69.50	81.99	40.96	<u>5.66</u>	5.83	<u>60.60</u>	54.33
SEext-Llama-2-7B-chat-25k+	21.37	26.68	34.63	35.47	<u>30.46</u>	15.51	27.51	21.30	25.87	68.50	78.79	41.29	3.90	3.50	59.69	53.83
Vicuna1.5-7B-16k*	19.4	26.1	38.5	25.3	20.8	9.8	27.9	22.8	27.2	<u>71.5</u>	<u>86.2</u>	40.8	6.5	4.5	51.0	43.5
SEext-vicuna1.5-7B-16k+	21.88	35.16	42.00	31.14	22.51	13.33	28.47	22.24	26.70	69.50	86.31	40.54	3.56	7.50	60.16	44.07
SEext-vicuna1.5-7B-25k+	<u>22.46</u>	<u>34.42</u>	42.58	30.95	24.33	12.72	27.75	22.26	27.21	72.00	84.02	40.38	3.01	7.00	58.86	43.86
Mistral-7B-ins-0.1(w/SWA)-16k+	19.40	34.53	37.06	42.29	32.49	14.87	27.38	22.75	26.82	65.00	<u>87.77</u>	<u>42.34</u>	<u>1.41</u>	28.50	<u>57.28</u>	<u>53.44</u>
MistralLite-16k+	32.12	47.02	44.95	58.5	47.24	31.32	33.22	26.8	24.58	71.5	90.63	37.36	3	54.5	66.27	65.29
SEext-Mistral-7B-ins-0.1-16k+	23.85	<u>37.75</u>	46.93	45.35	34.54	23.28	<u>30.45</u>	23.58	26.94	<u>69.50</u>	85.72	43.88	0.59	28.50	54.92	53.44
SOLAR-10.7B-instrcut-v1.0-4k+	16.5	24.06	46.76	44.03	36.05	22.76	31.39	19.81	26.36	70	87.91	42.49	4.5	26.5	41.04	54.36
SEext-SOLAR-10.7B-instrcut-v1.0-16k+	22.63	32.49	47.88	46.19	34.32	27.88	30.75	22.1	25.62	74.5	89.04	42.79	4	28	53.73	56.47



*Figure 4.* Passkey retrieval scores (accuracy) for Mistral-7binstruct-0.1 with SWA and Mistral-7b-instruct-0.1 with Self-Extend applied. For all input sequence length (token limit) from 4k to 24k and all depth, Self-Extend keeps a 100% Passkey retrieval score. Mistral-7b-instruct-0.1 with SWA nearly cannot retrieve the passkey out of the sliding window (the default sliding window size is 4096 by Mistral's configuration file).

radt, 2023), the passkey is placed with various document depths (where the passkey is placed in the input texts) and context lengths (ranging from 4k to 24k). For each depth of each context length, we performed multiple iterations of the passkey retrieval task with the passkey placed at a random location uniformly distributed across the interval

of a depth. To be more specific, ten iterations of passkey retrieval are performed for each span of 400. For example, if the document depth of 0.1 is tested for a context length of 8k, the passkey would be randomly placed at a position between [800, 1600) in each iteration and a total of  $10 \times (8000 \times 0.1/400) = 20$  iterations are performed.

The results are shown in Figure 4. We can see, across all tested depth and context length, without any fine-tuning, Self-Extend can get a %100 passkey retrieval accuracy. The results also demonstrated that: although Mistral w/ SWA has low PPL beyond its pretraining context window, it can only access information (i.e. the passkey) within its sliding window. Considering the simplicity of this task, this result strongly suggests it still does not have true ability to handle long contexts.

This is mainly due to the fact PPL is computed by averaging over many tokens, and as long as the most tokens are modeled well, PPL will not be high. This is, as we discuss before, closely related to neighbor tokens. Information from neighbor tokens (e.g. tokens in the sliding window) can be enough for predicting most tokens, as well as a low PPL. Although, a few important tokens, which is related to the understanding of long context and answering questions, may not be predicted well.

#### 4.3. Performance on real long context tasks

Most existing works of context length extension rely on language modeling (measured by PPL) and synthetic tasks such as passkey retrieval to measure LLMs' real long context capabilities. However, such tasks cannot comprehensively reflect LLMs' long context capabilities. Passkey retrieval is too easy and LLM may not be able to handle long context well with low PPL.

To gauge long-context performance, we perform the evaluation using two real-world long context evaluation benchmarks: Longbench (Bai et al., 2023) and L-Eval (An et al., 2023). The results are listed in Table 2 and Table 3 Some results in these tables are reported from other literature, which is indicated by footnotes.

On the Longbench, for all three different base models and most datasets, with Self-Extend applied, compared to the counter part, the model can obtain significant performance boost (SEext-Llama-2-7B-chat vs. Llama-2-7B-chat; SExt-Mistral-7B-ins-0.1 vs. Mistral-7B-ins-0.1(w/SWA); SExt-SOLAR-10.5B-instruct-v1.0 vs. SOLAR-10.5B-instruct-v1.0). On several datasets, Self-Extend does not obtain performance improvement, such as MultiNews. We think it's mainly due to the length of such datasets is not that long, for example, MultiNews only has an average length of 2k. Or some tasks like PassageCount are not suitable for testing the model of this size (i.e. too challenging). Also, compared to many fine-tuned models, Self-Extend has comparable or even better performance. To be more specific:

Llama-2-7B: We use Self-Extend to extend Llama-2-7bchat's context window from 4k to 16k and 25k<sup>4</sup> with two different settings. Both of them are much better than Llama-2-7b-chat. They also have better performance than all finetuned counterparts on several datasets such as HotpotQA. On others, the performance is still comparable. Considering the good instruction following ability of vicuna (Chiang et al., 2023), we also extend vicuna1.5-7B from 4k to 16k and 25k. Its fine-tuning counterpart is vicuna1.5-7B-16k. Again, with Self-Extend, vicuna1.5-7B is much better than vicuna1.5-7B-16k and it's even one of the top models among all Llama-2-7b based models. On some datasets, we observed inferior performance of the 25k variant compared to the 16k one. This is due to the trade-off between a larger context window and position precision. With larger context window, the model can have access to more information. But at the same time, to have a larger context window, SelfExtend requires larger group size, which means more coarse position information and is harmful to the model.

**Mistral-7B**: We extend the context window of the instruction-tuned variant of Mistral-7b to 16k. We use the default setting for the Mistral baseline, which has the SWA applied. Self-Extend again significantly improves Mistral's long context abilities. MistralLite (amazon, 2023) is fine-tuned from Mistral-7b to obtain longer context window and has much better performance on most datasets. But *many of these datasets have been included in MistralLite's fine-tuning data*, such as NarrativeQA, Qasper and so on<sup>5</sup>.

**SOLAR-10.7B**: SOLAR-10.7B (Kim et al., 2023) is newly released and it has no fine-tuned variant for context window extension yet. We use Self-Extend to extend it from 4k to 16k and obtain substantial performance improvement.

On the LEval, the similar results are observed. Except using Mistral as the base model, Self-Extend achieves superior performance nearly on all datasets, whenever compared to some fine-tuning free baselines such as NTK or further trained baselines such as Longchat1.5-7b-32k and Vicuna1.5-7b-32k. For Mistral, we suspect the inferior performance mainly came from the prompt engineering. This is implied by the much worse performance of MistralLite compared to vanilla Mistral. We didn't do prompt engineering for Mistral. <sup>6</sup>

In a brief summary, for the two benchmarks, **even compared to methods requiring further fine-tuning, Self-Extend achieves comparable or the best performance**. Although, initially, we just expected that Self-Extend could be better than the base model without any extension methods. Considering that Self-Extend only takes effect during inference and does not do any fine-tuning or training. This is super surprising. Usually, learning based methods have better performance than methods without learning, not only for context window extension and LLMs, but for many other tasks and NNs.

#### 4.4. Performance on short context tasks

An ideal context length extension method should ensure that the performance on standard short-context tasks has no degradation. Following (Peng et al., 2023b), we use Hugging Face Open LLM Leaderboard (Gao et al., 2023) to evaluate SelfExtend's performance on five public benchmark

<sup>&</sup>lt;sup>4</sup>We don't extend it to some regular length like 32k due to our limited computation resources.

<sup>&</sup>lt;sup>5</sup>More details about MistralLite's fine-tuning data can be found at: amazon/MistralLite. At least, GovReport, QMSum, NarrativeQA, Qasper, QuALITY and HotpotQA are included. Meanwhile, Multi-passage QA and summarization tasks are also in its fine-tuning data. This may cause a violation to the zero-shot form

<sup>&</sup>lt;sup>6</sup>The performance on LEval seems sensitive to prompt engineering for these  $\leq$ 13B-level LLMs. For example, on some datasets, the vanilla vicuna-13b even has a much worse performance than vanilla vicuna-7b. On LEval, stricter tests will be conducted in the future on LEval.

Table 3. Exam evaluation results on some <b>closed-ended tasks</b> from L-Eval. <b>Tokens</b> denotes the maximum input context length.
indicates the results are from us and others are reported by L-Eval. The rows in the same color (orange, green, blue, and pink) represent
the models of those rows from the same base model. The best performance is in <b>bold</b> and the second best is <u>underlined</u>

Model	Tokens	Coursera	GSM	QuALITY	TOEFL	CodeU	SFiction	Avg.
Claude1.3-100k	100k	60.03	88.00	73.76	83.64	17.77	72.65	65.97
GPT-4-32k	32k	75.58	96.00	82.17	84.38	25.55	74.99	73.11
Turbo-16k-0613	16k	63.51	84.00	61.38	78.43	12.22	64.84	60.73
Chatglm2-6b-8k	2k	43.75	13.00	40.59	53.90	2.22	54.68	34.69
XGen-7b-8k (2k-4k-8k)	2k	26.59	3.00	35.15	44.23	1.11	48.43	26.41
Chatglm2-6b-8k	8k	42.15	18.00	44.05	54.64	2.22	54.68	35.95
Chatglm2-6b-32k	32k	47.81	27.00	45.04	55.01	2.22	57.02	39.01
XGen-7b-8k	8k	29.06	16.00	33.66	42.37	3.33	41.40	27.63
MPT-7b-65k	8k	25.23	8.00	25.24	17.84	0.00	39.06	19.22
Llama2-7b-chat	4k	29.21	19.00	37.62	51.67	1.11	60.15	33.12
Longchat1.5-7b-32k	32k	32.99	18.00	37.62	39.77	3.33	57.02	31.45
Llama2-7b-NTK	16k	32.71	19.00	33.16	52.78	0.00	<b>64.84</b>	33.74
SelfExtend-Llama2-7B-chat+	16k	35.76	<b>25.00</b>	<u>41.09</u>	<u>55.19</u>	1.11	57.81	35.99
Vicuna1.5-7b-16k	16k	<b>38.66</b>	19.00	39.60	55.39	5.55	60.15	<u>36.39</u>
SelfExtend-Vicuna1.5-7B+	16k	<u>37.21</u>	<u>21.00</u>	<b>41.58</b>	55.39	<u>3.33</u>	<u>63.28</u>	<b>36.96</b>
Llama2-13b-chat	4k	35.75	39.00	<b>42.57</b>	60.96	1.11	54.68	39.01
Llama2-13b-NTK	16k	<u>36.48</u>	11.00	35.64	54.64	1.11	63.28	33.69
Llama2-13b-NTK(Dyn)	16k	30.08	<b>43.00</b>	<u>41.58</u>	<u>64.31</u>	1.11	35.15	35.87
SelfExtend-Llama2-13B-chat+	16k	<b>38.95</b>	<u>42.00</u>	41.09	<b>66.17</b>	1.11	63.28	<b>42.10</b>
Mistral-7b-ins-0.1 w/ SWA+	16k	<b>44.77</b>	44.00	<b>46.53</b>	60.59	2.22	<b>64.06</b>	<b>43.70</b>
MistralLite+	16k	29.23	32.00	<u>46.04</u>	17.47	3.33	14.06	23.69
SelfExtend-Mistral-7b-ins-0.1+	16k	<u>39.68</u>	<b>49.00</b>	<u>45.54</u>	60.59	1.11	<u>38.28</u>	<u>39.03</u>
SOLAR-10.7b-Instruct-v1.0+	4k	48.84	72.00	59.90	77.32	4.44	69.53	55.34
SEext-SOLAR-10.7b-Instruct-v1.0+	16k	<b>50.44</b>	72.00	<b>70.30</b>	<b>79.18</b>	4.44	<b>73.44</b>	<b>58.30</b>

*Table 4.* Performance of SelfExtend on Hugging Face Open LLM benchmark suite compared with two original Llama 2 baselines. For SelfExtend, we set the group size as 5 and the neighbor window as 1024.

Size	Name	ARC-c	Hellaswag	MMLU	TruthfulQA	GSM8k
7B	Llama 2	53.24	78.51	46.30	38.96	14.33
7B	SelfExtend-Llama 2	53.32	78.54	46.32	39.00	14.10
7B	Llama-2-chat-4k	53.07	78.41	48.32	45.24	18.95
7B	SelfExtend-Llama-2-chat-16k	52.56	78.43	48.34	45.33	18.42

tasks. Specifically, we use 25-shot ARC-Challenge (Clark et al., 2018), 10-shot HellaSwag (Zellers et al., 2019), 5-shot MMLU (Hendrycks et al., 2020), 0-shot TruthfulQA (Lin et al., 2021) and 5-shot GSM8K (Cobbe et al., 2021). The results are shown in Table 4. SelfExtend has nearly no influence on these short-context tasks.

Moreover, because the proposed SeldExtend does not do any fine-tuning and only takes effect during inference, Self-Extend is plug-in and can be dynamic. This means while encountering short text sequences, SelfExtend can be automatically and inherently disabled. Then, with the parameters unchanged, **the LLM can maintain its original performance on those short contexts scenarios**. Although we didn't intentionally to gain such advantages, this is the additional benefit from SelfExtend, compared to other finetuning based methods, for such methods usually undergo performance degradation on short-context tasks (Peng et al., 2023b; Xiong et al., 2023).

#### 4.5. Ablation Study

We also construct an experiment to investigate the influence of different choices of the group size G and the neighbor window  $w_n$ . The ablation study is constructed on two real-



Figure 5. Performance of Llama-2-chat-7b using SelfExtend with varied parameters on GSM100 and Quality. "> 16k" in this figure means all tokens out of the neighbor window are in the same group. Generally, on Quality, smaller group size leads to better performance, while both large and small neighbor window sizes will cause decreased performance. On GSM100, the impact is less clear. This is potentially due to the suboptimal prompt design in the benchmark. But notably, a very small neighbor window causes a drastic performance drop.

world datasets from LEval: GSM100 and Quality. GSM100 is not that long. It has an average length of 5.5k and the maximum length of 6k. Quality is longer and has an average length of 7k. Its maximum length is 8.5k. We don't choose super long datasets because we want to cover small group size (G). With G = 4,  $w_n = 2048$ , Llama-2-chat, equipped with SelfExtend, can handle sequences with lengths less than 10k. We summarize the results in Figure 5.

# 5. Conclusion and Discussion

In this paper, we argue that a LLM itself has the inherent ability to handle long sequences and it should be able to extend the context window size without any fine-tuning. Based on this belief, in a fine-tuning-free way, we propose Self-Extend to elicit the inherent long context abilities for LLMs by simply mapping unseen relative positions into those seen during pretraining via the FLOOR operation. We conducted thorough experiments to investigate the effectiveness of Self-Extend, including the language modeling task, the synthetic Passkey Retrieval task, and two real-world benchmarks. Although without any tuning or further training, the proposed Self-Extend can effectively improve LLMs' long context performance. More surprisingly, Self-Extend even beats existing fine-tuning-based methods on many datasets. These results highlight the potential of LLMs to handle long contexts and may inspire more in-depth research about the inherent abilities of LLMs.

*Limitation:* The limitation of the proposed Self-Extend includes the lack of implementation of Flash Attention (Dao et al., 2022) and the performance degradation with too large group size, which means the context window still cannot be extended to infinity with current SelfExtend. Meanwhile, like many regular tasks, there is still no consensus at present about how to do evaluation for long context tasks, which may cause problematic evaluation results.

*Future Work:* For future work, we will implement Flash Attention for Self-Extend to enhance its efficiency. We are also interested in testing SelfExtend on models using other positional encoding. Larger models, longer context and more challenging tasks will be tested if we can have access to more computational resources in the future. In the meantime, more sophisticated mapping methods will be considered as the replacement of the simple FLOOR operation, so as to achieve better long context understanding abilities and longer extended context window length.

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